AFRL-AFOSR-VA-TR-2016-0034

INFERRING STRUCTURE AND FORECASTING DYNAMICS ON EVOLVING NETWORKS

Jeffrey Brantingham
UNIVERSITY OF CALIFORNIA LOS ANGELES

01/05/2016
Final Report

Air Force Research Laboratory
AF Office Of Scientific Research (AFOSR)/ RTA2
Arlington, Virginia 22203
Air Force Materiel Command

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
21-12-2015

2. REPORT TYPE
Final Performance Report

3. DATES COVERED *(From - To)*
Sep 30, 2010 - Sep 29, 2015

4. TITLE AND SUBTITLE
MURI: INFERRING STRUCTURE AND FORECASTING DYNAMICS ON EVOLVING NETWORKS

5a. CONTRACT NUMBER

5b. GRANT NUMBER
FA9550-10-1-0569

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
PI: Brantingham, P. Jeffrey.

Co-PIs: Bertozzi, Andrea L.; Breiger, Ronald; Chang, Yu-han; Galstyan, Aram; Lerman, Kristina; McBride, Michael; Mezic, Igor; Milward, Brinton; Morrison, Clayton; Percus, Allon; Tita, George E.

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
UCLA Office of Contract and Grant Administration
11000 Kinross Ave, Suite 102
Los Angeles, CA 90095-1406

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Air Force Office of Scientific Research/NL
801 North Randolph Street
Room 732
Arlington, VA 22203-1977

10. SPONSOR/MONITOR'S ACRONYM(S)
AFOSR

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Public Release DISTRIBUTION A

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Networks lie at the heart of social organization and are central to the emergence and perpetuation of adversarial threats. Complex interactions between evolving network topologies and dynamic socio-cultural processes present immense challenges for countering such threats. This interdisciplinary MURI was positioned at the interface between social, mathematical and computational approaches to networks with goals of developing (1) stable metrics for inferring network structures, (2) forecasting dynamical social and information processes on networks, and (3) predicting the outcomes of network interventions. Major progress was made in measuring and modeling spatio-temporal event patterning in relation to network structures, event inference on networks, community detection and classification, processes of network formation, information spread and dynamical games on graphs, and experimental manipulation of social networks in laboratory settings. The MURI was grounded in empirical data on human activity patterns, crime event patterning, social media processes and observations collected through controlled laboratory and online experimental platforms.

15. SUBJECT TERMS
social networks; social media; crime; insurgency; terrorism; mathematical models; computational algorithms; network topology; dark networks; criminal gangs; community detection; network dynamics; information contagion; laboratory experiments

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	UU	48	P. Jeffrey Brantingham
					19b. TELEPHONE NUMBER *(Include area code)* 310-267-4251

Reset

INSTRUCTIONS FOR COMPLETING SF 298

1. REPORT DATE. Full publication date, including day, month, if available. Must cite at least the year and be Year 2000 compliant, e.g. 30-06-1998; xx-06-1998; xx-xx-1998.

2. REPORT TYPE. State the type of report, such as final, technical, interim, memorandum, master's thesis, progress, quarterly, research, special, group study, etc.

3. DATES COVERED. Indicate the time during which the work was performed and the report was written, e.g., Jun 1997 - Jun 1998; 1-10 Jun 1996; May - Nov 1998; Nov 1998.

4. TITLE. Enter title and subtitle with volume number and part number, if applicable. On classified documents, enter the title classification in parentheses.

5a. CONTRACT NUMBER. Enter all contract numbers as they appear in the report, e.g. F33615-86-C-5169.

5b. GRANT NUMBER. Enter all grant numbers as they appear in the report, e.g. AFOSR-82-1234.

5c. PROGRAM ELEMENT NUMBER. Enter all program element numbers as they appear in the report, e.g. 61101A.

5d. PROJECT NUMBER. Enter all project numbers as they appear in the report, e.g. 1F665702D1257; ILIR.

5e. TASK NUMBER. Enter all task numbers as they appear in the report, e.g. 05; RF0330201; T4112.

5f. WORK UNIT NUMBER. Enter all work unit numbers as they appear in the report, e.g. 001; AFAPL30480105.

6. AUTHOR(S). Enter name(s) of person(s) responsible for writing the report, performing the research, or credited with the content of the report. The form of entry is the last name, first name, middle initial, and additional qualifiers separated by commas, e.g. Smith, Richard, J, Jr.

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES). Self-explanatory.

8. PERFORMING ORGANIZATION REPORT NUMBER. Enter all unique alphanumeric report numbers assigned by the performing organization, e.g. BRL-1234; AFWL-TR-85-4017-Vol-21-PT-2.

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES). Enter the name and address of the organization(s) financially responsible for and monitoring the work.

10. SPONSOR/MONITOR'S ACRONYM(S). Enter, if available, e.g. BRL, ARDEC, NADC.

11. SPONSOR/MONITOR'S REPORT NUMBER(S). Enter report number as assigned by the sponsoring/ monitoring agency, if available, e.g. BRL-TR-829; -215.

12. DISTRIBUTION/AVAILABILITY STATEMENT. Use agency-mandated availability statements to indicate the public availability or distribution limitations of the report. If additional limitations/ restrictions or special markings are indicated, follow agency authorization procedures, e.g. RD/FRD, PROPIN, ITAR, etc. Include copyright information.

13. SUPPLEMENTARY NOTES. Enter information not included elsewhere such as: prepared in cooperation with; translation of; report supersedes; old edition number, etc.

14. ABSTRACT. A brief (approximately 200 words) factual summary of the most significant information.

15. SUBJECT TERMS. Key words or phrases identifying major concepts in the report.

16. SECURITY CLASSIFICATION. Enter security classification in accordance with security classification regulations, e.g. U, C, S, etc. If this form contains classified information, stamp classification level on the top and bottom of this page.

17. LIMITATION OF ABSTRACT. This block must be completed to assign a distribution limitation to the abstract. Enter UU (Unclassified Unlimited) or SAR (Same as Report). An entry in this block is necessary if the abstract is to be limited.

AFOSR FINAL PERFORMANCE REPORT

Project Title: Inferring Structure and Forecasting Dynamics on Evolving Networks.

AFOSR Grant No. FA9550-10-1-0569

Performance Period: September 30, 2010 – September 29, 2015.

Principal Investigator: Dr. P. Jeffrey Brantingham (branting@ucla.edu)

Lead Institution: University of California Los Angeles

AFOSR Program Manager: Benjamin A. Knott, 703-696-1142 benjamin.knott.2@us.af.mil

Abstract:

Networks lie at the heart of social organization and are central to the emergence and perpetuation of adversarial threats. Complex interactions between evolving network topologies and dynamic socio-cultural processes present immense challenges for countering such threats. This interdisciplinary MURI was positioned at the interface between social, mathematical and computational approaches to networks with goals of developing (1) stable metrics for inferring network structures, (2) forecasting dynamical social and information processes on networks, and (3) predicting the outcomes of network interventions. Major progress was made in measuring and modeling spatio-temporal event patterning in relation to network structures, event inference on networks, community detection and classification, processes of network formation, information spread and dynamical games on graphs, and experimental manipulation of social networks in laboratory settings. The MURI was grounded in empirical data on human activity patterns, crime event patterning, social media processes and observations collected through controlled laboratory and online experimental platforms.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE (*DD-MM-YYYY*)	2. REPORT TYPE	3. DATES COVERED (*From - To*)
21-12-2015	Final Performance Report	Sep 30, 2010 - Sep 29, 2015

4. TITLE AND SUBTITLE MURI: INFERRING STRUCTURE AND FORECASTING DYNAMICS ON EVOLVING NETWORKS	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER FA9550-10-1-0569
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) PI: Brantingham, P. Jeffrey. Co-PIs: Bertozzi, Andrea L.; Breiger, Ronald; Chang, Yu-han; Galstyan, Aram; Lerman, Kristina; McBride, Michael; Mezic, Igor; Milward, Brinton; Morrison, Clayton; Percus, Allon; Tita, George E.	**5d. PROJECT NUMBER**
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) UCLA Office of Contract and Grant Administration 11000 Kinross Ave, Suite 102 Los Angeles, CA 90095-1406	**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Air Force Office of Scientific Research/NL 801 North Randolph Street Room 732 Arlington, VA 22203-1977	**10. SPONSOR/MONITOR'S ACRONYM(S)** AFOSR
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Public Release

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Networks lie at the heart of social organization and are central to the emergence and perpetuation of adversarial threats. Complex interactions between evolving network topologies and dynamic socio-cultural processes present immense challenges for countering such threats. This interdisciplinary MURI was positioned at the interface between social, mathematical and computational approaches to networks with goals of developing (1) stable metrics for inferring network structures, (2) forecasting dynamical social and information processes on networks, and (3) predicting the outcomes of network interventions. Major progress was made in measuring and modeling spatio-temporal event patterning in relation to network structures, event inference on networks, community detection and classification, processes of network formation, information spread and dynamical games on graphs, and experimental manipulation of social networks in laboratory settings. The MURI was grounded in empirical data on human activity patterns, crime event patterning, social media processes and observations collected through controlled laboratory and online experimental platforms.

15. SUBJECT TERMS

social networks; social media; crime; insurgency; terrorism; mathematical models; computational algorithms; network topology; dark networks; criminal gangs; community detection; network dynamics; information contagion; laboratory experiments

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON / 19b. TELEPHONE NUMBER (*Include area code*)
U	U	U	UU	48	P. Jeffrey Brantingham 310-267-4251

Table of Contents:

I. Summary of Program Objectives & Outcomes:

The UCLA MURI focused on bridging gaps between mathematical and social science approaches to the study of social networks. We developed and deployed methods that are mathematically rigorous, connected to rich ethnographic context, and explicitly designed for working with social network data infused with real-world imperfections. Success in all three of these domains is ultimately necessary to ensure use of research-derived tools by decision makers in the field.

Social networks are seen as a key target of analysis for understanding the hybrid threats we face today. Exerting influence on social networks may serve to mitigate those threats. However, social networks are challenging to analyze because they are not only continuously evolving, but also are frustratingly messy in real-world settings. The key challenges of this MURI were to : (1) develop stable metrics to characterize network structures given that our observations of those networks are often fleeting and imperfect; (2) forecast dynamical processes operating on networks where the network topology itself may be evolving rapidly; and (3) predict outcomes of different interventions in networks where those interventions represent decisions made under conditions of uncertainty. The project fused both the collection of and work with real-world empirical data on social networks with careful formal mathematical and computational model development.

Over the course of the project we had productive conversations with AFRL researchers and demonstrated transition capability, with MURI research (predictive policing) currently in use by local law enforcement agencies. The MURI team was recognized for its work through extensive coverage in the popular and scientific media and through appointments in prestigious societies including the American Mathematical Society, the American Academy of Arts and Sciences, the Society for Industrial and Applied Mathematics, and Institute of Mathematical Statistics. The team amassed an impressive publication record with 123 papers published or in press and an additional 21 papers under review at the close of the project. The MURI program supported 63 postdoctoral fellows and PhD students, 11 MA students and more than a dozen undergraduates.

II. Accomplishments/Findings:

The following sections summarize key accomplishments and findings in each of our main challenge areas. Results in each challenge area are grouped into one or more topics. Key papers are identified at the head of each topical group with citations given both in “author-date” and numeric format corresponding to the list of references at the end.

A. Inferring Network Structure

The challenges to inferring social network structures such as node centrality and linkage patters are extreme under realistic empirical conditions. Empirical field observations and even social media feeds produce snapshots of social networks that are biased often to unknown degrees. The stability of network metrics under variable data conditions is poorly known. Our MURI focus on inferring network structure is aimed at developing metrics that will work with known limitations

under real field conditions. Three broad topical areas have been investigated to date: (1) Human Activity and Event Patterning; (2) Comparing Local and Global Properties of Networks; (3) Community Detection and Classification; (4) Infilling Missing Data in Network Contexts.

1. Spatio-Temporal Activity and Event Patterning

MOTIVATION: Social network characteristics frequently must be inferred *indirectly* from human activity patterns. The MURI team has focused on empirically and theoretically evaluating human spatio-temporal activity patterns as a basis for understanding how such patterns are facilitated by and/or contribute to the formation of social networks.

a) *Ecological Modeling of Gang & Criminal Activity*

Key Papers: Brantingham 2013 [8], Brantingham et al. 2012 [11], and Smith, Bertozzi et al. 2012 [100]

Brantingham (2013) uses a classical ecological model—Charnov's Prey Selection Algorithm—to study the target selection behaviors of Los Angeles car thieves. A key question in human activity event patterning is the degree to which such pattern is driven by opportunistic interactions with heterogeneous environments. Here the hypothesis is tested that the availability of different types of cars overrides other decision making parameters such as the perceived value or dangers of stealing particular cars. Surveys of Los Angeles streets shows that the majority of cars are targeted in proportion to their natural abundance. Only a tiny fraction of cars appear to be stolen because they are easy to steal or because they are especially valuable (in cultural if not monetary terms). The predominantly opportunistic nature of crime is potential important to consider when studying the relationship between social network characteristics and criminal event patterning.

Research teams have looked at ecological models as a foundation for understanding the spatial activity patterns and target choice decisions made by criminal offenders. Brantingham et al. (2012) adapt the classical Lotka-Volterra competition equations to predict the spatial distribution of violence between criminal street gangs, who are known to be tied together in a complex rivalry network. Empirical evidence from Hollenbeck Division, Los Angeles matches model predictions and leads to the conclusion that gang territories form as a byproduct of completion among rival groups. Most gang research assumes the opposite that competition and violence is a byproduct of territoriality. The research also suggests that interventions that seek to reduce the level of animosity among network rivals may have the unintended consequence of (temporarily) increasing the volume of conflict simply because reduced animosity produces more opportunities to interact.

Smith et al. (2012) adapt a more complicated model of animal territoriality to study gang behavior. In this case it is a PDE advection-reaction-diffusion system used previously to study coyote and wolf pack territories given constraints of natural terrain, and dynamic fluctuations in prey density and urine marking of multiple packs. Here gangs are distributed on an urban landscape. Features of the urban terrain (e.g., freeways) hinder local diffusive motion, while interactions with rival gang members and the graffiti markings of one's own and rival gangs

create advection gradients. The model is used to generate expected rivalry networks, territory distributions and activity patterns. Smith et al. (2012) compare model results with empirical data from Hollenbeck finding good parallels with territory and activity pattern distributions.

b) Accurate Density Estimation

Key Papers: Woodworth et al. 2014 [121] and Kostic and Bertozzi 2013 [61]

Standard density estimation techniques for point events do not incorporate priors informed by additional spatial data. Without such priors, density models of residential burglaries, for example, can predict events where there are no residences. Incorporating the spatial data can inform the valid region for the density. Learning and enforcing correlation between spatial data and event data can yield better estimates from fewer events. Woodworth et al. (2014) propose a non-local version of maximum penalized likelihood estimation based on the H1 Sobolev seminorm regularizer that computes non-local weights from spatial data to obtain more spatially accurate density estimates.

Kostic and Bertozzi (2013) develop methods to estimate a probability density based on discrete spatial point data via segmentation techniques. Since point data may represent certain activities, such as crime, the method can be successfully used for detecting regions of high activity. In this work a binary segmentation version of the well-known Maximum Penalized Likelihood Estimation (MPLE) model is used, as well as a minimization algorithm based on thresholding dynamics originally proposed by Merriman, Bence and Osher. Computational examples include the characterization of the probability density for residential burglary data from the San Fernando Valley in Los Angeles.

c) Spatio-Temporal Patterns and Processes

Key Papers: Mohler, Short, Brantingham et al. 2011 [83], Mohler, Short, Malinowski et al. 2015 [82] and Lewis et al. 2011[68], Fonoborevo et al. 2013 [24] and Fonoborevo et al. 2012 [25]

Mohler et al. (2011) introduce an epidemic-type aftershock sequence (ETAS) model to characterize spatio-temporal crime patterns. They develop a fully nonparametric version of the model with an expectation maximization (EM) method for model fitting and show that it outperforms nonparametric kernel density estimation (i.e., hotspotting) methods at predicting crime. Mohler et al. (2015) report on deployments of a parametric version of the ETAS model in randomized controlled field trials with the Los Angeles Police Department and Kent Police (UK). They find that real-time deployments predict twice as much crime as existing best practice. When predictions are used by officers in the field the ETAS model also prevents twice as much crime under normative deployment levels.

Lewis et al. (2011) characterize temporal patterns of violent civilian deaths in Iraq. These patterns are expected to evolve on time-scales ranging from years to minutes as a result of changes in the security environment on equally varied time-scales. To assess the importance of multiple time-scales in evolving security threats, they develop a self-exciting point process model similar to that used in earthquake analysis. Here the rate of violent events is partitioned into a background rate and a foreground self-exciting component. Background rates are assumed

to change on relatively long time-scales. Foreground self-excitation, in which events trigger an increase in the rate of violence, is assumed to be short-lived. The model is explored using data from Iraq Body Count on civilian deaths between 2003 and 2007. The results indicate that self-excitation makes up as much as 37–50 per cent of all violent events and that self-excitation lasts between two and six weeks, depending upon the district in question.

Key Papers: Fonoborevo et al. 2013 [24] and Fonoborevo et al. 2012 [25]

Fonoberova et al. (2013) follow up on an agent-based model of crime and civil violence presented in Fonoberova et al. (2012). In the earlier work, they observed that proportion of law enforcement officers required to maintain a steady level of criminal activity increased with the size of the population of the city and that the number of criminal/violent events per 1,000 inhabitants of a city shows non-monotonic behavior with size of the population. They developed a massive agent-based model (>10^6 agents) to study the mechanistic basis for these trends. The model encodes the relationship between an agent's perceived risk of capture and the legitimacy of the state authority (represented by police). Thus, even risk averse individuals can be recruited to hostile action when the perceived legitimacy of the state is low. In the model, global outbursts of criminal/violent activity are seen in small cities. Spatio-temporally distributed outbursts of criminal activity in large cities. Bigger cities thus need a larger ratio of law enforcement officers than smaller cities to navigate between decentralized outbursts. Fonoberova et al. (2013) present an important analysis of this model, reducing the agent-based model to a simple differential form. Sensitivity analysis is then preformed on the reduced model. Model reduction to rigorous mathematical form is an important innovation that is necessary to establish the policy relevance of agent-based models.

Key Papers: Raghavan, Galstyan et al. 2013 [90] and Raghavan, Ver Steeg et al. 2014 [91]

Raghavan, Galstyan et al. (2012) and Raghavan, Ver Steeg et al. (2014) develop a family of models to track the for the activity profile of a terrorist group, detecting sudden spurts against a baseline of pattern. A d-state hidden Markov model (HMM) captures the transition between latent states characterized as Active and Inactive. Two strategies for spurt detection and tracking are developed: A model-independent strategy that uses an exponentially weighted moving-average (EWMA) filter to track the strength of the group, as measured by the number of attacks, and a state estimation strategy that exploits the underlying HMM structure. The EWMA strategy is robust to modeling uncertainties and errors and readily tracks changes that last for a sufficiently long duration. The state estimation strategy offers the advantage that it tracks even changes in the state of the terrorist group that last for only a short. Case-studies with real terrorism data from open-source databases are provided to illustrate the performance of the two strategies.

d) Change Point Detection

Key Papers: Banerjee et al. 2013 [3], Tartakovsky and Pollack (2011) [103], Tartakovsky, Niloforov et al. (2015) [104] and Tartakovsky, Pollack and Polunchenko (2012) [105], Tartakovsky [106], Polunchenko and Tartakovsky 2012 [86], and Polunchenko, Sokolov and Tartakovsky 2014 [87]

The papers by Raghavan et al. are closely related to ULCA-MURI work focused on quickly detecting the point at which a sequence of events (e.g., interactions on a network) changes state from one rate constant to another. The key challenge in so-called change point detection problems is to detect such changes as fast as possible with a low false alarm rate.

2. Comparing Local and Global Properties of Networks

MOTIVATION: Many mathematical models of graphs and networks focus on asymptotic results, where we are interested in the steady state having assumed an infinite graph size. In real-world settings, social networks are finite and our observations of them often highly localized. Understanding how the local perception of networks compares to their global properties has important implications for our choice of metrics to characterize network structure and how network dynamics operate.

a) Local Network Paradoxes

Key Papers: Hodas, Kooti and Lerman 2013 [39], Kooti, Hodas and Lerman 2014 [58], Gupta, Yan and Lerman 2015 [34] and Lerman, Yan and Wu 2015 [67]

Hodas, Kooti et al. (2013) focus on ego networks, or that portion of a network that is visible to an individual node. Ego networks often display very different structural properties from the global network to which the node belongs. The local structure of ego networks also appears to induce unusual paradoxes such as the Friendship Paradox whereby your friends on average have more friends than you do. Kooti, Hodas et al. (2014) derive a strong tests of the Friendship Paradox based on median statistics, where most of your friends have more friends than you. Gupta et al. (2015) show that these paradoxes carry through to a number of standard network metrics and are systematic in their behavior. Lerman, Yan et al. (2015) provide a means to quantify the magnitude of what they define more generally as the ‘majority paradox’.

3. Community Detection and Classification

MOTIVATION: Many approaches to detecting communities are derived from studies of very large networks, with applicable asymptotic results. Under such conditions, community structure can often be accurately recovered. The reality, however, is that most social networks observed ‘in the wild’ are not only small (few observed individuals) but also sparse (few observe links). It is an open question whether accurate community affiliations can be recovered under such poor data conditions.

a) Mathematical Innovations in Community Detection

Key Papers: Bertozzi and Flenner 2012 [4], Van Gennip and Bertozzi 2012 [109], Merkurjev, Kostic, et al. 2013 [79] and Merkurjev, Garcia-Cordona, et al. 2014 [80], Van Gennip, Guillen et al. 2014 [108]

Bertozzi and Flenner (2012) develop a set of novel methods to accomplish graph segmentation. Segmentation is the process of partitioning a set of elements into unique groups. Here nodes of a graph are segmented into two communities. Their method is a class of variational algorithms that combine recent ideas from spectral methods on graphs with nonlinear edge/region detection methods traditionally used in in the PDE-based imaging community. The algorithms require the minimization of the Ginzburg-Landau functional, which combines a diffuse interface and a periodic double-well potential. The diffuse interface seeks to push the system towards a low entropy state with no defined communities, while the periodic potential seeks a high entropy state with every graph element combined with like-elements into one of two unique communities. Convex-splitting algorithms allow Bertozzi and Flenner (2012) to quickly find minimizers of the proposed model and take advantage of fast spectral solvers of linear graph-theoretic problems. Van Gennip and Bertozzi (2012) present a formal proof that the graph-based version of the Giznburg-Landau functional converges to a stable continuum (PDE) form.

Merkurjev, Garcia-Cordona et al. (2014) present a computationally efficient algorithm that combines a diffuse interface model, based on the Ginzburg-Landau functional, with an adaptation of the classic numerical Merriman-Bence-Osher (MBO) scheme for graph-based methods to solve a wide range of learning problems in data clustering and image processing. Van Gennip, Guillen et al. (2014) prove a key piece of the mathematical architecture for graph analogs of the MBO scheme. A graph curvature is derived from the graph cut function, the natural graph counterpart of total variation (perimeter). This derivation and the resulting curvature definition differ from those in earlier literature, where the continuum mean curvature is simply discretized, and bears many similarities to the continuum nonlocal curvature or nonlocal means formulation. This new graph curvature is not only relevant for graph MBO dynamics, but also appears in the variational formulation of a discrete time graph mean curvature flow.

b) Multi-class Community Detection and Network Modularity

Key Papers: Garcia-Cordona, Flenner et al. 2013a,b [27][28], Garcia-Cordona, Merkurjev, Bertozzi, et al. 2014 [29], and Hu et al. 2013 [42]

Most community detection work on graphs focuses on how to segment a social network into two known groups. The methods of Bertozzi and Flenner (2013), using the Ginzburg-Landau functional, accomplish this binary segmentation by pushing nodes into one of two energy potential 'wells'. Many real-world problems, however, require assigning elements of a social network to three or more groups. To deal with graph-based multiclass segmentation problems, Garcia-Cordona, Flenner et al. (2013) extend the Ginzburg-Landau double-well potential to a multi-well potential case, where the similarities between nodes is now based on some continuous distance metric among node attributes rather than simply binary distinctions. The method is semi-supervised in that a small fraction (1-2%) of nodes are known to belong to the same

community; but the metric 'value' of those communities is not known. *A priori* information provides a fidelity constraint that the algorithm must adhere to. The multi-class Ginzburg-Landau method achieves graph segmentation with minimal error (~5% or less) for hard problems that are either intractable with other methods (e.g., spectral clustering) or are only solvable with introduction of other information such as the metric 'values' associated with groups. Garcia-Cardona, Merkurjev et al. compare the multi-class Ginzburg-Landau segmentation method with a graph-based adaptation of the classical numerical Merriman-Bence-Osher (MBO) scheme, which alternates between diffusion and thresholding to achieve segmentation. They demonstrate the performance of both synthetic data, grayscale and color images. Both methods are competitive with or better than the current state-of-the-art multiclass segmentation algorithms. Garcia-Cardona, Murkurjev, Bertozzi et al. (2014) introduce multiclass segmentation combining the Ginzburg-Landau Functional with the Gibbs simplex.

Hu et al. (2013) provide novel mathematical insights into network modularity. Network modularity is a very influential metric for understanding the structure of communities in a larger network context. Hu et al. (2013) reveal deep mathematical connections between network modularity and compressive sensing by formulating community detection as an energy minimization problem. The research opens the door to the use of a branch of variational mathematics that is completely unique in the study of networks.

c) Constraints on and Empirical Applications of Community Detection

Key Papers: Melamed et al. 2013 [78], Breiger et al. 2014 [9], Ver Steeg, Galstyan and Allahverdyan 2011 [111], and Van Gennip, Hunter et al. 2013 [107]

Graphs are inherently flexible in the types of information that they can represent. The most familiar graph structures show the links between a single category of elements such as a people. However, graphs may also be composed of mixtures of different categories of objects such as people, groups and events. Links within such multi-mode graphs show the connections across data types; the groups with whom individuals are allied and the events in which both individuals and groups are involved. Melamed et al. (2013) extend spectral clustering methods to deal with multi-mode networks. They apply the methods to an instance of community conflict over the construction of a sports stadium where nodes represent people, issues and 'games' or strategic agendas. The resulting multi-modal communities reveal the 'games' that holds actors together. Breiger et al. (2013) adopt a related approach in looking at two-mode network involving terrorist groups and narcotics trafficking. Importantly, they find that there are multiple 'recipes' by which terrorist organizations may successfully engage narcotics trafficking, one type exploiting strong territorial and population control, but another emphasizing quick, ephemeral exploitation of opportunities.

Semi-supervised graph segmentation or community detection frequently focuses on injecting *a priori* information about the specific community affiliation of individual nodes. Such information may be available in field surveillance contexts, but other constraints are also possible. Ver Steeg, Galstyan and Allahverdyan (2011) study semi-supervised clustering where there is *a priori* information on which pairs of nodes must link or cannot link, but the specific group affiliation of individuals is not known. The distinction is subtle, but important. *A priori* information on which individuals share a link does not necessarily mean that they are members

of the same group. The link may also be an 'out group' link. When such pair-wise linking constraints are present, but at low density, there is a minimum detection threshold—a minimum number of known links (cannot links) that must be present to detect communities—but the threshold is significantly lower than without any constraints. When a large enough number of constraints are present the detection threshold vanishes. This study provides a guide for the number of field observations of social interactions (links) necessary to successfully classify individuals into communities.

Van Gennip et al. (2013) provide a worked example of using two types of empirical constraints for community detection. Given geo-social field observations of gang members is it possible to correctly assign individuals to gangs with little or no a prior information on actual gang identities? The field observations arise from Los Angeles Police Department 'field interviews' where officers have interacted with known or suspected gang members at a specific location and time (i.e., geospatial constraint) and the individuals involved in the stop are recorded as being present together if two or more people are there (i.e., social link constraint). Note that the later constraint is the same as that investigated by Ver Steeg, Galstyan and Allahverdyan (2011) in that being stopped together does not guarantee membership in the same gang, a fact strikingly born out by the empirical data. Van Gennip et al. (2013) start by constructing a similarity graph for the 809 individuals stopped in 2009. The similarity graph differentially weights the importance of geospatial and social information. A spectral clustering method is then used to identify clusters among the 809 individual in the graph, corresponding to unique gangs groupings in Hollenbeck. Model clusters are then compared with the LAPD's knowledge of the individuals' actual gang membership. Using geospatial stop locations only, spectral clustering yields gang clusters where 56% of individuals in a group actually belong to the same gang (44% of individuals in the assigned group actually belong to one or more of the 30 other gangs in the area). This high degree of purity from spatial-only information in part reflects the importance of territories to Los Angeles street gangs. Adding in a small amount of social information—who was stopped with whom—can improve the purity of clusters to a large degree, but the social data must not be too sparse. Theoretical exploration shows the sparsity levels at which social information improves the ability to identify gang affiliations. For example, one must typically observe more than 10% of social interactions before social information improves upon geospatial observational data only, depending upon the amount of outgroup interaction. The intelligence implications of this work is that one can identify group affiliations from observations limited to the locations visited and who is seen with whom.

d) Stochastic Block Models

Key Papers: Dabkowski et al. 2015 [19], Ver Steeg, Moore, et al. 2014 [117]

Dabkowski et al. (2015) develop a means for fitting generalized block models (community groupings) given multiple relational measures among dyads (e.g., individuals a, b and c claim one another as friends, while a and b play on the same basketball team and c on a different team). Block modeling with multiple relations is typically and NP-hard problem. Ver Steeg, Moore et al. (2014) tackle community detection for stochastic block models using a zero-temperature Bethe-Peierls approximation. Equivalently, they study a message-passing algorithm where the distribution of messages is concentrated on the most likely label of each node.

e) Community Detection from Interactions and/or Node Properties

Key Papers: Cucuringu 2014 [17], Lerman and Ghosh 2012 [64], and Smith, Zhu, Lerman et al. in press 2015. [101]

Cucuringu (2014) develops a method for clustering of communities based on the degree of similarity or 'synchronization' between node attributes. Lerman and Ghosh (2012) study a very similar problem of node synchronization in a network of coupled oscillators, finding that the network synchronizes in stages corresponding to its topological structure. Smith et al. (2015) extend the elegant MAP equation as an efficient entropy-based method for including node attributes along with link structure in identifying communities.

f) Node Attributes in Network Contexts

Key Papers: Cucuringu 2015 [16], Cho, Ver Steeg and Galstyan 2013 [12], and Purcell and Rombach 2015 [89]

The attributes of individual nodes is certainly influenced by their local network context. Cucuringu (2015) develops a model for inferring relative ranking agents (e.g., teams, players, gangs) given observations of the dyadic interactions among them. Cho, Ver Steeg and Galstyan (2013) tackle the relationship between real-world spatial and network positions of individuals. They develop a method to classify social media users according to activity in locations defined by latent signatures seen in their social media posts.
Purcell and Rombach (2015) examine a special case of the graph coloring problem. Here so-called role coloring of a graph G is an assignment of colors to the vertices of G such that two vertices of the same color have identical sets of colors in their neighborhoods. For example, suppose we color the vertices of G red or blue. If this coloring is a role coloring then for all red vertices u and v we have that u has a blue neighbor if and only if v has a blue neighbor. The problem of finding a role coloring with $1 < k < n$ colors is NP-hard for planar graphs. Restricting the problem to trees yields a polynomially solvable case, as long as k is either constant or has a constant difference with n, the number of vertices in the tree. Co-graphs are always k-role-colorable for $1 < k \leq n$ and construct such a coloring in polynomial time.

g) Core Periphery Structures in Networks

Key Papers: Lee, Cucuringu and Porter 2014 [62]

Lee et al. (2014) develop topological (link density) and transport-based metrics for core-periphery structures in networks, with applications to real-world transportation networks.

h) Clustering in Social Media Data

Key Papers: Ma, Flenner et al. 2015 [70]

Ma et al. (2015) use a data fusion methods to combine images, text and large-scale open source text and image databases (e.g., Wikipedia). They then use topic modeling methods to discern latent structures in the data.

4. Infilling Missing Data in Network Contexts

MOTIVATION: The above community detection and classification methods were all focused on the fundamental problem of assigning individuals to specific positions in a social network given observations of those individuals and their activities. Here we single out a related, but special class of problems where events need to be attributed to individuals or groups and then assigned to a position in a social network. In many cases there is missing information that needs to be inferred given the pattern of activities themselves.

a) Infilling Event, Location and Link Data

Key Papers: Stomakhin et al. 2011 [102], Hegemann et al. 2013 [36], Cho et al. 2013 [13][114], Zipkin et al. 2015 [123], Intagorn and Lerman 2014 [43], Narang et al. 2013 [84], Zhu and Lerman 2014 [122]

Many shooting events known to the police lack complete information about the parties involved. In data from the Hollenbeck Division in Los Angeles, for example, only 31% of 1208 gang-related shootings have both the victim and suspect gang known. A full 62% have only the suspect or victim known, while 7% identify neither suspect or victim. Interrupting gun violence could be made more effective if the missing information could be recovered using the data on hand. Stomakhin et al. (2011) leverage the fact that gang violence frequently occurs over a network of rivals to make inferences about the most likely pair of gangs to which a single event belongs. Assuming that retaliatory violence follows a self-exciting Hawkes process, participant identities can be reconstructed using a computationally effective algorithm that maximizes an energy functional under a set of reasonable constraints. This capability is demonstrated using simulated data. They discover that the performance of the method is deeply connected to the parameters of the Hawkes process in question, and in certain parameter regimes may predict the correct participants with very high likelihood.

The work of Stomakhin et al (2011) showed that known gang activity between rivals can be modeled as a self-exciting Hawkes point process on an edge of the rivalry network. Even when data is incomplete, localized excitations in parts of the known dataset can help identify which edges and therefore which gangs were involved. Hegemann et al. (2012) remedy one limitation of the previous study, namely the assumption that the parameters of the Hawkes process underlying gang violence are known. In reality these parameters have to be estimated from the data itself. They propose an iterative method that simultaneously estimates the parameters in the underlying point process and assigns weights to the unknown events with a directly calculable score function. The results of event classification using simulated data are comparable to those of Stomakhin et al. (2011) without having make any a priori assumptions about model parameters.

Cho et al. (2013) make two additional contributions to the problem of attributing gang identities to gang shootings. They propose a spatial-temporal latent point process model—not just the temporal only Hawkes process model—that describes geographically distributed, self-exciting interactions between pairs of entities. An efficient approximate algorithm based on variational expectation-maximization is used to infer unknown participants in an event given both the location and the time of the event. The model is validated both synthetic and real–world gang data. Concentrating on the 375 events where both the suspect and victim gang identities are

known, Cho et al. (2013) deliberately mask a fraction of the identities and then seek to recover those identities using the proscribed method. Even when only 150 of the 375 events have known gang affiliations (i.e., 60% missing data) the spatio-temporal latent point process model successfully identifies the true gangs involved in the events more than 50% of the time. With 20% missing data, the method identifies the correct gang more than 65% of the time. The random chance of identifying the true gangs is around 3%. These methods may augment detailed street intelligence in identifying who is involved in hostile acts using easy-to-gather data on the spatio-temporal distribution of events.

Zipkin et al. (2015) adopt a similar approach in the study of missing information in electronic communications records. Such communications exhibit bursts of activity localized in time. A self-exciting Hawkes process model is used in combination with a relaxed maximum likelihood method for filling in missing data. The method is demonstrated using a data set composed of email records from a social network based at the United States Military Academy.

Intagorn and Lerman (2014) present a method for inferring user location from the text content of social media posts. The method performs as well as naïve Bayes and provide a means to quantify the error of that estimate.

Link prediction leverages information in network structure to identify unobserved links or predict new links that will form in the future. Narang et al. (2013) examines link prediction from the novel perspective of network flows and shows that different types of flows lead to different notions of network proximity, some of which are mathematically equivalent to existing link prediction heuristics. Link prediction heuristics based on a random walk-type processes outperform the popular Adamic-Adar and the number of common neighbors heuristics in many networks.

Zhu and Lerman (2014) approach link prediction from the point of view of name discovery. Specifically, a user v creates a link to another user u after seeing u's name on his or her screen; in other words, visibility of a user (name) is a necessary condition for new link formation. They propose a model for link prediction that estimates the probability a user will see another user's name, and use this model to predict new links. The work suggests that the effort required to discover a new social contact is negatively correlated with link formation, and the easier it is to discover a user, the higher the likelihood a link will be created.

B. Forecasting Dynamics on Evolving Networks

The challenges associated with inferring network structure are compounded by the recognition that those networks themselves may be constantly evolving. Not only might the numbers of nodes and links in the network change over time, but also their specific wiring patterns and node and link attributes can be highly dynamic. To leverage social network analysis for AFOSR missions it is necessary to understand how networks evolve over time and how dynamic processes operate over those networks. Four topical areas have been investigated in this domain: (1) Models of Network Formation; (2) Correlation and Causation in Networks; (3) Interaction

Between Network Topology and Network Dynamics; (4) Information Spread in Online Social Networks; (5) Team Formation; (6) Games of Graphs; (7) Sacred Values and Legitimacy in Network Interactions; (8) Network processes in Geo-Social Context.

1. Models of Network Formation

MOTIVATION: Empirical analysis of network structures provides insights into their origin and function. Being able to repeatedly generate instances of such networks from first principles gives an important theoretical benchmark for comparison with empirical cases. For example, if networks that reliably and faithfully capture structural properties of real world networks can be generated mathematically or via simulation, then replicative experiments can be performed on those artificially generated graphs. One can then investigate what is theoretically possible with a given network type, rather than simply what is empirically observed in the real-world.

a) Theoretical Models of Two-Mode Network Formation

Key Papers: Melamed et al. 2013 [82], Breiger et al. 2014 [12], Bradonic et al. 2010 [7], and Cho, Ver Steeg & Galstyan 2011 [15]

Many social and physical phenomena can be modeled as two-mode or, more generally, multi-modal graphs. For example, the spread of a disease through a population may be represented as a two-mode network of people and the places that they visit. Analysis of empirical multi-modal networks provide insight into their structure and function, as illustrated in work by Melamed et al. (2013) and Breiger et al. (2013) for this this MURI. Bradonjic et al. (2010) examine generative models of two-mode networks, or bipartite graphs using their terminology. The generative model in question is a Random Intersection Graph (RIGs). RIGs generates connections between nodes n (mode-1) and list of one or more attributes m (mode-2), with any one node connected to an attribute with independent probability p drawn from some specified distribution. Two nodes n_i and n_j are considered to be connected only if they are liked to the same attribute in m. Bradonjic et al. study the component evolution of RIGs and give the conditions for the formation of a giant component, where all nodes are connected in a single graph structure.

Cho, Ver Steeg and Galstyan (2011) study a very similar problem. Here network nodes are characterized by a vector of attributes, which evolve depending upon links to other nodes. The links themselves evolve in response to node attributes. Cho et al. develop an expectation maximization (EM) approach and use it with a Co-Evolving Mixed-Membership Block Model to infer the dynamic process driving network evolution given observations of node attributes and links only. They are able to predict the gowning polarization of the US Congress over time by looking at bill co-sponsorship patterns; links between senators are drawn if they co-sponsored 3 or more bills together during the period of observation (97^{th} to 104^{th} Senates).

b) Modeling Gang Network Growth

Key Papers: Hegemann et al. 2011 [35]

Hegemann et al. (2011) propose an agent-based model to simulate the creation of street gang rivalries. The movement dynamics of gang agents are coupled to an evolving network of gang rivalries, which is determined by previous interactions among agents in the system. Basic gang data, geographic information, and behavioral dynamics suggested by the criminology literature are integrated into the model. The major highways, rivers, and the locations of gangs' centers of activity influence agent motion. Data from the Hollenbeck Division of the Los Angeles Police Department is used as a case study to test the model. The resulting Simulated Biased Levy Walk Model (SBLN) replicates the empirical rivalry network among the 31 known Hollenbeck gangs at least as well as computationally simpler Geographic Threshold Graphs and Brownian Motion Networks. The SBLN also matches the spatial density of gang violence crime reasonably well. It better captures the mobility dynamics of gang members. Such models could be use to predict how rivalry networks will evolve with the introduction or removal of specific gangs.

2. Correlation vs. Causation in Networks

MOTIVATION: A persistent problem in social network analysis is disentangling why two nodes within a network share similar attributes. It is possible that the similarity is due to one node directly influencing the other node thereby generating the similarity because of the social network connection. It is also possible that there is no causal influence between nodes, but rather two nodes link to one another because they are already similar or because they achieve similarity independently through connection to some latent variable outside of the social network. For example, it is well known that if one individual is a smoker then another individual to whom she is connected is also more likely to be a smoker. However, it is not clear that peer pressure directed from individual one to individual two is the cause of individuals two habit. The two individuals may have become friends because they were both smokers before hand, or because both were independently influenced by seeing magazine advertisements for cigarettes. A similar challenge faces two members of the same gang are violence: Is it because the social relationship acquired through the gang enhanced their violent tendencies, or because previously violent individuals self-selected into the gang.

a) Hidden Variables and Tests for Information Transfer Over Networks

Key Papers: Ver Steeg and Galstyan 2011 [111], Ver Steeg and Galstyan 2013a [112], Ver Steeg and Galstyan 2012 [110], and Ver Steeg and Galstyan 2013b. [115].

Many widely studied graphical models with latent variables lead to nontrivial constraints on the distribution of the observed variables. Inspired by the Bell inequalities in quantum mechanics, Ver Steeg and Galstyan (2011) develop a 'hidden variable test' that allows one to rejected the hypothesis that correlations between nodes in a network is due to the presence of a latent variables outside of the network. They introduce a sequence of relaxations which provides progressively tighter hidden variable tests. They demonstrate that the method rules out latent homophily as the sole explanation for correlations in information content on the media news aggregator Digg.com. In Ver Steeg and Galsytan (2013b [AISTATS]) they present a more general method that searches for the optimal test for latent homophily. The mathematical underpinnings are conceptually simpler, and lead to a more tractable optimization (a linear program versus a semidefinite program).

Ver Steeg and Galstyan (2012) also develop methods to detect causal information transfer between nodes; a complement to rejecting the possibility that similarity between nodes is due to correlation with a latent variable. Here they use a measure of causal relationships based on the information–theoretic notion of transfer entropy, or information transfer. This theoretically grounded measure is based on the temporal dynamics of information spread, and allows a natural, predictive interpretation. Causal networks inferred by transfer entropy can differ significantly from static friendship networks because most friendship links are not useful for predicting future dynamics. They demonstrate through analysis of synthetic and real–world data from social media websites that transfer entropy reveals meaningful hidden network structures. In addition to altering our notion of who is influential, transfer entropy allows us to differentiate between weak influence over large groups and strong influence over small groups.

In a extension of their work in 2013b, Ver Steeg and Galstyan 2013a use information transfer to directly quantify the strength of the effect of one user's content on another's in a model-free way. It emphasis on model-free measurement is important because the interactions among people in social media typically depend on idiosyncratic features of the social media platforms themselves such as platform-specific cues and capabilities. Estimating this transfer entropy in this context is made possible by combining recent advances in non-parametric entropy estimation with sophisticated tools for content representation. Using Twitter data collected for thousands of users, content transfer is able to capture non-trivial, predictive relationships even for pairs of users not formally linked in the social network graph. Information transfer as a measure makes large quantities of previously under-utilized social media content accessible to rigorous statistical causal analysis.

Key Papers: Ver Steeg, Galstyan, F. Sha, S. DeDeo 2014 [113]

Ver Steeg et al. (2014) highlight a paradox in information theoretic clustering whereby clustering results for small sample sizes appear far more reliable than clustering results from large sample sizes. They link this paradox to a fundamental flaw in clustering methods based on a mutual information criterion. Specifically, mutual information clustering prefers to split the probability mass into arbitrary but equal-sized masses, completely ignoring the data's intrinsic structure. Ver Steeg et al. (2014) present a solution to this paradox in building an information theoretic metric for clustering that is consistent under coarse-graining of the data.

Key Papers: Fellouris and Tartakovsky 2012 [21], Fellouris and Tartakovsky 2013a [22] and Fellouris and Tartakovsky 2013b [23]

Fellouris and Tartakovsky (2012, 2013a, 2013b) focus on optimal methods for sequentially testing nodes in a network for the presence of some information. The optimal solution minimizes the number of nodes (or time) needed to reject the hypothesis that the information is absent.

3. Interaction Between Network Processes and Structure

MOTIVATION: Most traditional measures of network structure, especially those deployed in social science research, consider network topology alone as the basis for measuring such things as node influence. It is clear, however, that network characteristics such as the influence of a

node need to take into account the type of process operating over the network. For example, a node in the exact same topological position may have little influence if the process operating over the network is simple diffusion (random walk), but tremendous influence if the process is a contagious epidemic.

a) Inter-Organizational Networks

Key Papers: Popp et al. 2014 [88]

Provide an overview of network structures and functions in the context of business and government organizations.

b) Non-Conservative Diffusion Processes

Key Papers: Lerman and Ghosh 2011 [31], Ghosh and Lerman 2014 [30], Smith, Lerman et al. 2013 [98], Ghosh and Lerman 2015 [32], and Ghosh, Lerman, Teng et al. 2014 [33]

Lerman (co-PI) and her team have carefully delineated the interaction between network topology and network processes that may be either conservative or non-conservative, where a quantity transmitted over the network is conserved (e.g., a fixed money supply) or grows/shrinks (e.g., number of computers infected by a virus), respectively. In a series of papers (see Lerman and Ghosh 2011; Ghosh and Lerman 2014), they have demonstrated with formal mathematical analysis that standard network centrality metrics such as Google's Page-Rank are implicitly based on a process of conservative diffusion (random walk) over the network structure. Common sense appraisal of social media dynamics, empirical observation of social media sites such as Twitter an Digg, and mathematical analysis shows that the process of information spread on the internet is better characterized as a non-conservative epidemic process where the representation of information within the system grows with each transmission event. Page-Rank and other centrality metrics based on assumption of conservative processes incorrectly identify central nodes as compared with empirical based measures of influence. They then prove that an alternative metric, Bonicich alpha-centrality, is mathematically derivable from a non-conservative diffusion process. The implication is that this metric should better capture centrality for networks that support epidemic processes; a hypothesis confirmed in comparisons with empirical measurement of node influence on both Twitter and Digg graphs. Lerman and Gosh (2012) explore an alternative measure of network structure that tracks the timing at which different portions of the network synchronize when the coupling between oscillators (nodes) is driven by an epidemic type non-conservative process. Different structures within the network are exposed by different synchronization models Note that, even though we may recognize that network topology and dynamics interact, it is still much easier to observe topology than process. As a consequence, it is important to attempt to develop stable metrics that work from observable topology alone, but are responsive to the type of processes operating on the network. Alpha-centrality accomplishes this goal, whereas the synchronization methods do not. The tunable parameter 'alpha' in the alpha-centrality metric allows investigation of how different length-scales of interaction on the network (e.g., reflecting how far an epidemic can spread) change the picture of which nodes are most central.

Smith, Lerman et al. (2013) demonstrate the mathematical equivalence of epidemic diffusion (a replicator process) on graphs and the normalized graph Laplacian operator with edges reweighted by eigenvector centrality of nodes. More weight is given to edges connecting to more central nodes. The graph Laplacian, $L = D - A$ with D being the degree matrix of the graph and A the adjacency matrix, is the standard mathematical form for representing conservative diffusion (random walk) on a graph. The work by Smith, Lerman et al. is thus extremely important for demonstrating a elegant mathematical relationship between conservative and non-conservative diffusion processes on graphs, but also opens the door for very efficient graph metrics based on a well known differential operator. They develop a worked example of a new spectral clustering technique using the replicator version of the graph Laplacian. The replicator gives preference to cliques and clique-like structures, enabling it to more effectively discover communities that may be obscured by dense intercom- munity linking.

Ghosh and Lerman (2015) turn to an empirical case of opinion dynamics in the context of network synchronization. Opinion dynamics are modeled as non-conservative diffusion on the network. Network synchronization is modeled after systems of coupled oscillators. They find that nodes synchronize their opinions faster when they are topologically clustered in the same community. Ghosh, Lerman Teng et al. (2014) take this idea and show how observations of opinion dynamics can be used to map measure the quality of community classifications.

c) Self-Exciting and Swarming Processes on Networks

Key Papers: Short, Mohler, Brantingham and Tita 2014 [96], Von Brecht et al. 2013 [119], Allahverdyan and Galstyan 2014 [1], and Hogg, Lerman and Smith 2013 [41]

Short, Mohler, Brantingham and Tita investigate stochastic network models of criminal street gangs. Here network links are defined by violent exchanges between groups, which occur as a result of (1) different background animosities, (2) a drive for retribution, and (3) third party dampening effects—where an attack by Gang C causes Gang A to divert its focus away from its most recent rival Gang B. All three effects are documented empirically in the gang research literature. The model is formalized as a combination of self-exciting/self-inhibiting point processes, which allows for the study of the generation of rivalry networks among groups of two or more gangs. A key insight from this work is that gang rivalry networks with third party dampening effects may only take a limited number of forms: (1) all gangs fighting equally with one another, essentially creating a fully connected graph; (2) rivalries consisting of combinations of dyads and triads that only fight within their local networks; and (3) combinations of dyads and triads with single gangs that randomly shift their attacks among all other gangs. Higher order network structures involving rivalries of four or more gangs are not stable. Typically, dyads that are locked in battle have the highest rivalry intensity, followed by triads who cycle in their violent attacks. Complete rivalry networks lead to random violence, but at a lower overall rate. Simulated interventions in these point-process networks leads to some counter-intuitive outcomes. In a system of seven gangs organized into two stable dyads and one stable triad, knocking out a gang with the single highest rivalry intensity drives the system towards three stable dyads. The post-knockout configuration results in a higher total amount of crime. One implication is that interventions might seek to destabilize dyads into triads, and triads into rivalries evenly divided among all gangs in the environment.

Von Brect et al. (2013) consider a network model involving attraction and repulsion, a conceptualization inspired by the mathematical study of swarms. For swarms it is well known that local interactions among mobile particles—try to be close but not too close to another particle—leads to the formation of macroscopic structures in the population such as rotating mills or pulsating disks. Here, spatially localized interactions are replaced by interactions on a fixed network structure. The dynamic problem to be solved is given by attraction and repulsion to scalar values as a node attribute—be close to but not too close to the attribute value of others you are linked to. In the case of a complete graph, where all agents are coupled to all other agents, the system has a lowest energy state in which half of the agents agree upon one value and the other half agree upon a different value. This is a two-group consensus. When the network among the N agents occurs according to an Erdos-Rényi random graph $G(N, p)$, where p is the independent probability of connection between any two nodes, the stability of the two-group consensus is preserved for probabilities greater than $p^* = O(\log N)$. In other words, relatively few interactions are needed to preserve stability of the consensus state. The empirical implication is that distinct opinions can be maintained through a relatively simple mechanism (attraction and repulsion) operating over relatively sparse social networks.

Allahverdyan and Galstyan (2013) examine a problem that is conceptually a form of swarming in opinion formation. They formulate a rule for updating the subjective probabilistic opinion of one agent in the light of the opinion a partner. The rule follows the ideas of semantic information theory: the agent does not react to partner's opinions that are either far from his current opinion (confirmation bias to unexpected information) or coincide with it (no new information). The update rule is studied under different interaction scenarios. The model displays an order of presentation effect: when consecutively exposed to two conflicting opinions, perhaps through interactions with different nodes in a network, a preference is given to the last opinion encountered. It is also shown that the agent can employ its confirmation bias for reducing cognitive dissonance and defending his opinion when interacting with a self-assured partner.

Hogg, Lerman and Smith (2013) present a stochastic model for user actions on a social media site that invokes stochastic transitions between different user states. The stochastic model leads to better predictions of user behavior than is the case for regression models without such state transitions.

4. Information Spread in Online Social Networks

MOTIVATION: Online social networks continue to increase their penetration of human public and private social life. Despite the central role they now play there is much that we do not understand about the dynamics of information spread in online contexts. Developing the ability to forecast and influence online social networks will depend upon not only a clear empirical picture of online interactions, but also reliable mathematical models that explain those processes.

a) Empirical Characterization of Information Spread

Key Papers: Ghosh and Lerman 2011 [35], Ver Steeg, Ghosh and Lerman 2011 [116], Hodas and Lerman 2012 [37], Hodas and Lerman 2014 [38], and Kooti, Aiello, et al. 2015 [59]

The recognition that online social network activity is often better approximated by a epidemic, non-conservative diffusion process was inspired in part by empirical study of social interaction patterns on media sites Twitter and Digg. Their empirical work has grown in scope to encompass detailed assessments of the macro- and microscopic characteristics of information cascades and the predictability of user posting behavior. Gosh and Lerman (2011) develop a comprehensive quantitative framework for analyzing the size (total number infected) and diameter (path lengths) of epidemic outbreaks (cascades) associated with the spread of a given piece of information. Generally such outbreaks are log-normally distributed in size (not power-laws) and reach far fewer people than would be expected from a pure epidemic model. Ver Steeg, Gosh and Lerman (2011) observed on the social media site Digg that information spreads fast enough for one initial spreader that it should infect hundreds of people, given a standard epidemic model. Yet on average cascades end up affecting only 0.1% of the entire network. They identify two effects, previously studied in isolation, that combine to drastically limit the final size of cascades. First, because of the highly clustered structure of the Digg network, most people who are aware of a story have been exposed to it by multiple friends. This topological structure lowers the epidemic threshold while moderately slowing the overall growth of cascades. Second, despite multiple opportunities for infection within a social group, people are *less likely* to become spreaders of information with repeated exposure. The opposite is true with a biological vector; infection probability increases in the number of exposures. The consequences of this mechanism become more pronounced for more clustered graphs. Ultimately, repeatedly severely curtails the size of social epidemics on Digg.

Hodas and Lerman (2012) suggests that attention limitation also plays an important role in limiting spread of online information. Using URLs as markers of unique memes or packets of information, they study of retweeting patterns, the primary mechanism by which information spreads on the Twitter follower graph. The patterns of behavior are best describe by a "principle of least effort" combined with limited attention. Specifically, users retweet information only when it is most visible and therefore most convenient to act upon. As that information declines in visibility—as new tweets appear—the probability that it is retweeted declines rapidly. Hodas and Lerman (2012) propose that a user's limited attention is divided among incoming tweets, providing novel evidence that highly connected individuals may be less likely to propagate an arbitrary tweet. Hodas and Lerman (2014) show empirically that social contagion is unlike biological contagion in that repeated exposures to the same information decreases the probability of its spread. Information that is repeatedly pushed to users overloads their limited attention capacity.

Kooti, Aiello et al. (2015) study more than 2 million users and 16 billion emails to understand how email volume impacts response time. They confirm what we all intuitively know, namely as the number of emails received increases the number of emails that receive a response decreases, response length declines, though the emails that do receive a reply tend to receive it more quickly.

Key Papers: Lerman, Intagorn et al. 2012 [65]

Modeling the dynamics of information spread in online contexts also creates the opportunity to develop reliable predictors of such behavior. Lerman, Intagorn et al. (2012) study network

proximity as a basis for predicting behavior. In principal, people who are "close" in some sense within a social network are more likely to perform similar actions than more distant people. They compare the performance of different proximity metrics including neighborhood overlap, but find that that metrics that take into account the attention-limited nature of interactions in social media lead to substantially better predictions.

5. Teams, Cooperation and Competition

MOTIVATION: Networks create opportunities for cooperation and competition among individuals. How such interactions emerge given the constraints of the network are fundamental for optimizing function.

a) Modeling Teams

Key Papers: Dykhuis et al. 2013 [20]

Dykhuis et al. (2013) study a problem whereby individuals are endowed with a skill from some larger set of possible skills. Each individual is then given a task that requires multiple skills. They therefore need to form 'teams' that combine diverse skills to successfully complete the tasks. In this case, teams can only be formed if individuals are directly connected in a social network. Dykhuis et al. find that random graphs perform just as well as complete graphs and that they achieve nearly optimal task completion much more efficiently (faster).

b) Authority, Cooperation and Competition in Religious Networks

Key Papers: McBride 2015a [72] and McBride 2015b [73]

McBride (2015a) examines authority in the context of coordination problems. Coordination devices are objects, individuals or institutions that create expectations about how others in a group will act. Through these expectations coordination devices are able to direct actions. Coordination devices therefore can be said to have authority in that they are able to direct action. Inverting this observation shows that authority arises when individuals or institutions are able to direct coordinated actions. The Mormon Church is treated as an example. Authority to direct action is created ritualistically in this context. McBride 2015b addresses a related issue of why churches need free riders. Game theoretic models suggest that free riders may be tolerated initially if they are the principal source of future cooperators.

c) Conflict vs. Negotiated Settlements

Key Papers: McBride and Skaperdas 2014 [76]

McBride and Skaperdas (2014) investigate theoretically and in laboratory experiments the subtle balance between conflict and negotiated settlement. When rivals cannot enforce long-term settlements only short terms compromises, there exists a temptation to engage in conflict today as it changes the relative strength of bargaining positions and the eventual outcome to favor one rival over another. Essentially fight now to ensure success in the long run. They find in laboratory experiments that subjects are more likely to fight now as the importance of the future increases.

6. Games on Graphs

MOTIVATION: Information spread in online social networks is often strategic in nature. How exactly player strategies and, more generally, game play operate in network contexts raises may open questions. How does network topology influence strategic choices? What types of networks will evolve among players given specific game forms and freedom to choose opponents/teammates?

a) *Game Theoretic Models of Criminals in Society*

Key Papers: Short, Brantingham and D'Orsogna 2010 [100] and D'Orsogna et al. 2013, [18]

Short et al. (2010) constructed an evolutionary 'adversarial' game to study the fundamental interactions between offenders who commit crimes and the victims who must choose whether report those crimes to the police. It is assumed that in a normally functioning society that reporting of a crime to the police may not guarantee a conviction, but it also does not bring retribution. In truth, the chance of retribution for reporting a crime (snitching) is a very real danger in many security settings. Short et al. (2010) find that for a spatial games, a critical threshold of 'upstanding citizens' who neither commit nor report crimes is necessary to drive society to a utopian state with no crime. Below this critical threshold only a special category of citizen, the "Informant" who will commit crimes but also report them, will drive a society to utopia. They find that the presence of even a single informant is sufficient to effect this transition.

D'Orsogna et al. (2013) experimentally study this adversarial environment in the laboratory with human subjects to test whether Informants are indeed critical for the emergence of cooperation. They find in these experiments that, even more so than predicted by theory, Informants are crucial for the emergence and sustenance of a high cooperation state. A key lesson is that successfully reaching and maintaining a low defection society may require the cultivation of criminals who will also aid in the punishment of others.

b) *Social Network Games*

Key Papers: Kim, Chi, Maheswaran, Chang (2011) [56], Li, Chang, and Maheswaran (2013) [69], and Ni, Chang and Maheswaran 2013 [85]

The Ultimatum Game is frequently played as a dyadic one-shot game. In it, an Offeror has an endowment of money, say $10, and they are obliged to offer a minimum of $1 and maximum $9 to the Respondent. The Respondent can accept or reject the offer, but if they reject then both players receive $0. The rational economic strategy is for the Offeror to offer the minimum and for the Respondent to accept without hesitation. In countless experiments conducted in a wide range of cultural contexts, it has been shown that humans never meet the expectations set forth for rational game play. A sense of fairness intrudes and drives Respondents to punish Offerors, at a cost to themselves, for making offers that they consider to be stingy. Chang and colleagues have created a novel experimental environment that turns the Ultimatum Game into a repeated social activity where players get to choose their partners at each turn, punishing unacceptable game play both by rejecting offers and by refusing to play with them. Cutthroat rational players

might also exploit the ability to change playing partners to their advantage. Kim, Chi, Chang, Maheswaran (2011) describe the game an introduce the concept of strategy entropy dynamics describing the variation in offer and accept values over the course of game play. Using this measure, they identify sub-populations of players including those may make wildly divergent offers early in game play (high entropy) and then settle down to stable offers later (low entropy). Other players may start with a stable strategy and become more variable in their offers as game play progresses. Still others may maintain high or low entropy in their strategies throughout game play.

Li, Chang, and Maheswaran (2013) introduce a Networked Resource Game, a graphical game where players' actions are constrained (or facilitated) by a set of resources that they can distribute over links in a graph. Distributing resources forms partnerships that yield rewards. Consider two players who are each endowed with an assortment of different colored cards. Player one has three different cards, one each in red, green and yellow. Player two has only two cards, one red and one green. Each player decides to allocate one card to the link between them. Payoffs are determined by which colors are played. For example, the pair red-red might yield a higher payoff than the pair red-green. Note that actions are constrained both by the numbers of cards that each player posses and the types of cards; i.e., quantity and quality of resources. Player one has more strategic options than Player two because they have a greater range of card types from the outset. Player one also has more cards in reserve, after allocating to Player 2, that they can allocate to more partnerships. Player 2's overall wealth is constrained by their lack of a yellow card, which conceivably could yield the highest payoffs depending upon the payoff structure of the game. Player 1 has the option to play this card. Given this game structure, Li et al. study through simulation how different social network structures—allocations of resources across links—impact the formation of equilibrium game solutions. The outcomes are analyzed in terms of social welfare and inequality, as measured by the Gini coefficient. In general, they find that more complete graphs lead to higher social welfare (lower inequality) for all graph topologies.

Ni, Chang and Maheswaran (2013) show in laboratory experiments with human subjects that human players tend to form many more network links in game play than is necessary to achieve optimal allocation of resources. This suboptimal behavior results from conflicting interests of players.

Key Papers: Kianercy, Galstyan, Allahverdyan 2012 [53], Kianercy and Galstyan 2012 [52], Juul, Kianercy and Galstyan 2013 [44], and Kianercy and Galstyan 2013 [51]

Kianercy, Galstyan, Allahverdyan (2013) investigate a model of strategic network formation in repeated games where players adopt actions and connections simultaneously using a simple reinforcement learning scheme. Under plausible assumptions the dynamics of such systems can be described by so called replicator equations that characterize the co-evolution of agent strategies and network topology. A comprehensive analysis is developed of a three-player two-action game, which is the minimum system size where structural dynamics are important. A complete characterization of Nash equilibria in such games is provided. They also determine the learning parameters domain in which a homogenous network is stable. In addition, we provide both simulation and analytical results suggesting that for N-player games the stable equilibria consist of star motifs as the main building blocks of the networks.

Social Experimental Games describe situations individuals have some measure of freedom to change partners over the course of repeated play. Kianercy and Galstyan (2012) introduce an important constraint by examining how agents explore the fit between their strategies and changing environmental conditions—payoffs determined by the fit between behavior and environment—when the actions by two players are mutually dependent. They find that, when agents differ in their rate of exploration of possible strategies during learning, multiple equilibria emerge. When players are equivalent in their rate of exploration there is only one stable global equilibrium exists. This study is a first step towards considering agents connected in a network of interdependencies interacting with a changing environment.

Juul, Kianercy and Galstyan (2013) study the case of social games with a population of strategies. Here there is turnover in the players such that experienced players leaving the game are replaced by naïve individuals with strategies drawn from some stationary set. The process yields a version of a replicator dynamic seen frequently in theoretical biology. It is shown that equilibria for a range of game types are not only shifted by the introduction of population turnover, but also can become unstable.

Game play in Juul et al. (2013) can be considered to take place on a fully connected network. Kianercy and Galstyan (2013) examine a related setting where a fixed population of players simultaneously evolve their strategies and network connections, which determines potential game pairings. Here they find that the system is also represented by the a replicator dynamic. They find that star-shaped networks and pure strategies are Nash stable when there is no exploration (or errors in strategy choice). When there is strategy exploration there is a threshold above which a fully connected network becomes stable.

7. Sacred Values and Legitimacy in Network Interactions

MOTIVATION: Traditional game theoretic models build expected outcomes based on the strategic choices of rational actors. Observations of real-world strategic interactions make clear, however, that individuals, groups and institutions choose actions are far from rational and may, in fact, be clearly against their own interest. So-called sacred or protected values may be one source of such seemingly irrational outcomes since, by definition, some behaviors are disallowed because the violate sacred values. Legitimacy surfaces in a related way in that some types of game play between actors may be feasible because one player considers the other legitimate—acceptable to their sacred value system—while other game play may be reserved for interactions with those they consider illegitimate—unacceptable in their sacred value system. More generally, legitimacy and sacred values may have an important an impact on social network games in that they (1) may constrain who is allowed to play with whom, and/or (2) what game moves are possible with different partners.

a) Sacred Value Networks

Key Papers: McCalla et al. 2013 [77]

McCalla et al. (2013) provide a practical definition of sacred values ground in social networks. They begin with the evolutionary adversarial game introduced by Short et al. (2010) and impose

a fixed (random) graph structure on the players in the game. Game play proceeds in the same way as in Short et al. except that criminal offender types (Villains and Informants) will not select anyone in their immediate social network—their first-order neighbors—as victims. Similarly, reporting types (Palladins and Informants) will not report on crimes committed by offenders in their immediate social network if called to do so. This behavior satisfies the definition of sacred values in that victimizing and reporting against first-order neighbors is prohibited. All other individuals in the population are fair game. McCalla et al. (2013) find that the introduction of sacred values so defined changes equilibrium arrangement of strategies. A stable semi-utopia exists composed of a larger number of Palladins, upstanding citizens who do not commit crime and will report crime, and smaller number of Informants, who both commit and report crime. Effectively sacred values provide protection for Informant criminals allowing them to persist. McCalla et al. (2013) extend the scope of sacred value networks to include criminal types linked to one another through other criminal types. Herein is a natural definition of a criminal gang. They find that the dynamics of this system produces a semi-dystopian equilibrium composed of a large number of Villains, followed in frequency by Apathetics (non-criminal, non-reporting), Informants and Palladins. This last equilibrium is a COIN worst case scenario; the two agent types who are most willing to help in restoring order are least frequent in the population. The protection offered by criminal gangs (or insurgents) by their broad sacred values network offers tremendous protection from both fellow gang members and peripheral civilians who receive some protection from their association with the gang.

b) Legitimacy and Sentiment

Key Papers: Schoon 2014 [95], Schoon 2015 [94], and Smith, Lerman and Kozareva 2013 [99]

Using fuzzy-set qualitative comparative analysis, Schoon et al. (2013) have looked at the relationship between state use of force in counter-insurgency campaigns and the outcomes of those campaigns in 30 different conflicts. The analysis concentrates on the conditions, measured in a half-dozen qualitative variables, that lead populations to perceive state use of force as legitimate or illegitimate. Schoon et al. find that there are many different configurations of conditions that may lead the use of force to be considered legitimate, but a much more narrow set of configurations that lead to a perception of illegitimate use of force. The implication is that it is easier to design COIN campaigns to avoid a perception of illegitimacy than to design operations to achieve legitimacy. Such distinctions are also clearly linked to the ultimate success of COIN. Schoon (2015) looks at the special case of the Kurdistan Workers Party (PKK) finding that the group exploited multiple-shifting sources of legitimacy to maintain resiliency over time.

Smith, Lerman and Kozareva (2013) use sentiment analysis to classify the position (for, against, neutral) expressed in a tweet about a controversial topic. The results are then used to study user behavior. Twitter is primarily used for spreading information to like-minded people rather than debating issues. Users are quicker to rebroadcast information than to address a communication by another user. Individuals typically take a position on an issue prior to posting about it and are not likely to change their tweeting opinion. One implication of the study is that Twitter supports the perpetuation of sacred values with little natural tendency for negotiating those values.

8. Social Media Processes in Geo-Social Context

MOTIVATION: Social media are often portrayed as operating in an aspatial world, where the physical distance between users is irrelevant to their activity online. If this were strictly true then the study of social network dynamics online would be of limited relevance to understanding the materialization of real-world threats. Evidence is emerging, however, that physical spatial processes play a very significant role in driving online social media activity.

a) Geographic Patterning in Social Media

Key Papers: Bora, Chang and Maheswaran 2014 [5], Bora, Zaytsev, Chang and Maheswaran 2013 [6], and Kooti, Lerman, Aiello et al. 2015 [60]

Bora et al. (2014) examine how racial segregation of the geographic spaces of three major US cities (New York, Los Angeles and Chicago) affect the mobility patterns of people living in them. Using over 75 million geo-tagged tweets from these cities, Bora et al. (2014) find a compelling amount of deviation in travel patterns when compared to artificially generated ideal mobility. A common trend for all races is to visit areas populated by similar race more often. Blacks, Asians and Hispanics tend to travel less often to predominantly white census tracts, and similarly predominantly black tracts are less visited by other races.

Bora et al. (2013) turn their attention to social media and gangs in Los Angeles. Over 10 millions geo-tagged tweets were used as observations of human movement and apply them to understand the relationships of geographical regions, neighborhoods and gang territories. Using a graph based-representation of street gang territories as vertices and interactions between them as edges, a machine learning classifier was trained to tell apart rival and non-rival links. The classifier correctly identify 89% of the true rivalry network, which beats a standard baseline by about 30%. Looking at larger neighborhoods, Bora et al. were able to show that distance traveled from home follows a power-law distribution, and the direction of displacement can be used as a profile to identify physical (or geographic) barriers when it is not uniform.

Kooti, Lerman and Aiello et al. (2015) show empirically that the attributes of users including the degree of their network connections to one another strongly influence their patterns of online purchases. Purchasing activity is higher among men and more affluent individuals, but women who share network connections make more purchases of similar items than those in isolation suggesting strong network influences.

C. Predicting Outcomes of Network Interventions

Networks are difficult to measure both in terms of their topology, which may be static or evolving, and the dynamical processes operating over those networks. Hostile networks may also have covert structures and processes that make detection and description particularly challenging. Consequently, there is considerable uncertainty involved in choosing the most appropriate ways to intervene in a network and what the outcomes of those interventions may be. A key challenge addressed in this MURI is therefore to develop and test models of the best ways

to impact networks. MURI work concentrated in three areas: (1) Characterizing the Resilience of Dark Networks; (2) Leveraging Cognitive Biases to Impact Information Spread; and (3) Experimental Interventions in Networks.

1. Characterizing the Resilience of Dark Networks

MOTIVATION: Dark or covert networks are not a post-9/11 phenomenon. Conflicts in a wide range of locations and from many points in history have produced dark networks and attempts to eradicate them. Understanding the diversity of potential responses of dark networks to external shocks is of critical important to understand how to deal with them in contemporary security environments.

a) *Empirical Case Studies of Dark Networks*

Key Papers: Bakker et al. 2011 [2], Milward 2014 [81]

A crucial policy question for governments is how to cope with "dark" networks that display a remarkable level of resilience when faced with targeted intervention. Based on an in-depth study of three cases (MK, the armed wing of the African National Congress in South Africa during apartheid; FARC, the Marxist guerrilla movement in Colombia; and the Liberation Tigers of Tamil Eelam, LTTE, in Sri Lanka), Bakker et al. (2011) outline how external shocks impact dark network characteristics (resources and legitimacy) and networked capabilities (replacing actors, linkages, balancing integration and differentiation), and how these in turn affect a dark network's resilience over time. Resilient networks by and large manage to weather external shocks by replacing actors and linkages through recruit new members into the network and that the legitimacy of the dark network in they eyes of local populations was critical to recruiting.

Milward (2014) critiques the assumption that networks are superior to organizations or markets as a means of coordination is wrong. If a problem can be dealt with effectively in a market or a single organization, healthcare leaders should do it, as it is much easier than organizing and sustaining a network. Dark networks are used as example to reveal the fragility of some network structures compared to organizations and markets.

2. Leveraging Cognitive Biases to Impact Information Spread

MOTIVATION: The most obvious way to impact networks is to knock out nodes or links, which results in differential network function. A complementary approach may be to structure information such that its dynamics on the network meet some specified goals. Information might be structured recognizing the impact of network topology on spread. It might also be designed to take advantage of human cognitive biases.

a) *Network and Information Design*

Key Papers: Lerman, Jain, Ghosh et al. 2013 [66], Hogg and Lerman 2012 [40] Lerman and Hogg 2014 [63], and Kang and Lerman 2013a [46], 2013b [48], 2013c [49], 2015a [45], 2015b [47], 2015c [50]

A series of papers by Lerman and her team turn to the idea of leveraging human cognitive biases to influence spread of information in online contexts. Lerman, Jain, Ghosh et al. (2013) propose a limited-attention version of the famous alpha centrality metric that recognizes both the non-conservative nature of information spread and also the overload that comes from repeated broadcasts of information to the same nodes. The apparent importance of nodes ranked by limited-attention alpha centrality conforms better to empirical measures of influence than other common metrics. Hogg and Lerman (2012) and Lerman and Hogg (2014) Provide empirical evidence for visibility effects on information spread in the social news aggregator site Digg. Lerman and Hogg (2014) take this one step further to propose how leveraging positional bias can improve peer recommendations in a social media example. Kang and Lerman Explore the relationships between individual cognitive processes and how those impact user interaction with and spread of information. In general, they find that models that incorporate cognitive biases such as 'positional bias', attention limitation and exposure limitations, outperform alternatives that do not include such biases.

3. Experimentally Impacting Networks

MOTIVATION: By definition dark networks are partially or completely covert. Not only does this raise serious questions about how to detect and understand the structure of dark networks, but also how we are to design, deploy and, ultimately, measure the impact of interventions in networks. Considerable speculation has surround, for example, which nodes of network to remove to have the greatest impact on the capacity of the network to mount hostile actions; some argue for peripheral nodes and others for central nodes. Controlled experiments offer a way forward to understand how to design interventions into networks and the likely outcomes of those interventions.

a) Optimal Knockout in Dark Networks

Key Papers: McBride and Hewitt 2012 [74] and McBride and Caldara 2013 [75]

McBride and his team at UC Irvine have conducted laboratory experiments with human subjects playing the role of a counter terrorism operator. The experimental task is to observe a terrorist or criminal network and make a decision about which node in the network to knock out to have the greatest impact on the ability of the network to engage in crime (McBride and Hewitt 2012). The terrorist network is "dark" in that only a fraction of the total possible links between network participants are observed; other links are presumed hidden from view by covert tactics. The game theoretic expectation is that the best strategy is to knock out the node with the maximum number of observed links, regardless of whether that node is officially under surveillance or not (the operator can observe the in-links of nodes not under surveillance, but not their out-links). Human subjects behave as expected when the network is not completely dark (66% of network under surveillance). However, when the network is extremely dark (11% of nodes under surveillance), a high fraction of human subjects react sub-optimally and choose a 'shot-in-the-dark' approach of randomly knocking out a node. Even where information quality is poor, the optimal strategy is to knock out the observed node with the maximum number of links. These experiments are very revealing of human decision making processes under conditions of uncertainty. The results have been replicated looking at the impact of how network topology is

presented to the counter terrorism operator, namely a graph structure or a table structure (McBride & Caldera 2012).

b) Simulating Exerting Influence in Dark Networks

Key Papers: Walsh et al. 2011 [122]

Walsh et al. (2011) consider a setting where a single "leadership agent" intervenes in a multi-agent system through actions that change (perhaps subtly) the dynamics of the system. Leadership algorithms are deployed so as to oversee classical 2-player games. This structure is then applied to leadership of a super-peer file sharing network. In these experiments the network contains some agents that make locally greedy decisions that hamper network function as a whole. A leader acting based on a more global criteria can push the system to a better equilibrium point as well as speeding up convergence. A mathematical approximation of such super-peer networks can be used to aid a leader in determining a minimum cost intervention strategy.

c) Influencing Social Network Games Using Artificial Agents

Key Papers: Kim, Chi, Ning, Chang, and Maheswaran 2012 [57], Kim, Chang, Maheswaran, Chi, Ning 2012 [55], Chang, Levinboim, Rajan, Maheswaran 2011 [11], Kim, Chang, Graham, et al. 2013 [54] and Frazier, Chang and Maheswaran 2012. [26]

Kim, Chi, Ning, Chang, and Maheswaran (2012) inject artificial agents or 'bots' playing different strategies into the Social Ultimatum Game to observe outcomes. Bots can be designed that subtly (i.e., are not rejected by human players), but effectively impact game play. Chang, Maheswaran, Levinboim, Rajan (2011) concentrate on the ability of 'bots' to mimic natural human game play. One bot called Marginal Value Optimization (MVO) was able to outperform all human players (and other bots) by being an attractive target for offers in the Social Ultimatum Game. Even though rewards from any one offer were smaller on average compared with human players, MVO was able to attract more offers and therefore garner a larger share of total rewards. The important conclusion here is that human game play can be potentially manipulated in online strategic social interactions to achieve desirable outcomes.

Kim, Chang, Graham, et al. (2013) investigate the role of moral values of Social Network Game play. Subjects were administered the 32-item Moral Foundations Questionnaire (MFQ), which measures the degree to which people value each of five foundations, Harm/Care, Fairness/Reciprocity, In-group/Loyalty, Authority/Respect, and Purity/Sanctity. The subjects then played the Social Ultimatum Game where, importantly, they were paired with mixtures of AI 'bots' who could directed to play decidedly generous, fair and stingy strategies. Kim et al. (2013) found that people searched for partners within the game network games who positively correlate with their own moral code, which is reflected in similar actions with respect to fair game. Preferences to forgive or punish unfair game play correlate with moral code, with 'liberal' codes more likely to punish and 'conservative' codes more likely to forgive.

Frazier et al. (2012) develop and deploy a team-networked game that can be played on a mobile device for an augmented-reality scavenger hunt. The authors explore the differences between the games in a virtual and the real-world environment and the impact of AI agents making

suggestions to the team based on locational cues. They find that 'activity' is much lower in the real-world setting, but that the presence of an AI agent can significantly enhance levels of activity.

d) Individual Utility Estimation & Impacting Networks

Key Papers: Carter and McBride 2013 [10], Ridinger, John, McBride and Scurich 2015 [93], and Ridinger and McBride 2015 [92]

Carter and McBride (2013) argue that the utility we infer from people's actions is potentially quite different from the utility that they perceive or experience, which has huge implications for the perceived impact of network interventions.

Ridinger, John et al. (2015) model a system where defenders have a network of targets that they have to protect. The defenders can decide to randomly distribute their effort over all targets, or use all of their effort on a single target (strategies are cost neutral). In the lab, human subjects then decide whether to attack one of the targets based on knowledge about the defender's strategy. When defender strategies are presented individually, the payoffs to attackers are equivalent. When given a choice to attack stationary or rotating defenders, attackers prefer the stationary system. Perceived risk and therefore deterrence may be dependent upon the sequence or process by which networked targets are projected.

Ridinger and MicBride (2015) show that games played with financial incentives impact estimates of their game-play partner's intentions (i.e., Theory-of-Mind) and that TOM is increased more in men than in women in the presence of increasing monetary rewards. This work is important for not only understanding how to interpret interactions in network contexts, but also for dynamical processes on networks.

III. Principal Investigators

UCLA (Lead)

Jeffrey Brantingham	Principal Investigator; Human Behavior Dynamics
Andrea Bertozzi	Variational Math, Swarms & Pattern Formation

UC Irvine

Michael McBride	Game Theory & Experimental Economics
George Tita	Criminal Networks & Street Gangs

USC ISI

Yu-han Chang	Multi-agent Networks & Decision Making
Aram Galstyan	Machine Learning, Causal Inference
Kristina Lerman	Social Dynamics in Online Networks

USC

Alex Tartakovsky (FY 1-3)	Change-point Detection & Statistical Inference

University of Arizona

Ronald Breiger	Social Networks & Institutions
Paul Cohen (FY 1-3)	Statistics of Network Security
Brinton Milward	Dark Networks
Clayton Morrison (FY 4-5)	

UCSB

Igor Mezic	Networked Dynamical Systems

Claremont Graduate University

Allon Percus	Statistical Physics & Random Graphs

IV. Awards & Recognition During Period of MURI:

P. Jeffrey Brantingham, UCLA Anthropology (PI)

National and Scientific press coverage for AFOSR-supported papers:

Mohler, George O., Martin B. Short, Sean Malinowski, Mark Johnson, George E. Tita, Andrea L. Bertozzi, and P. Jeffrey Brantingham. Randomized controlled field trials of predictive policing. *Journal of the American Statistical Association*, in press, 2015.

Van Gennip, Y., B. Hunter, R. Ahn, P. Elliott, K. Luhz, M. Halvorson, S. Reid, M. Valasik, J. Wo, G. E. Tita, A.L. Bertozzi , P.J. Brantingham. Community detection using spectral clustering on sparse geosocial data. SIAM Journal of Applied Math, 73(1): 67-83, 2013.

P.J. Brantingham, G.E. Tita, M.B. Short and S. Reid, The Ecology of Gang Territorial Boundaries, *Criminology*, 30:851-885 2012. doi: 10.1111/j.1745-9125.2012.00281.x

Mohler, G.O., M.B. Short, P.J. Brantingham, F.P. Schoenberg, and G.E. Tita, Self-exciting point process modeling of crime. Journal of the American Statistical Association 106(493):100-108, 2011. doi:10.1198/jasa.2011.ap09546.

Andrea Bertozzi, UCLA Mathematics (co-PI)

Honorary Degree, Doctor of Human Letters *honoris causa*, from Claremont Graduate University, 2014

Appointed Betsy Wood Knapp Chair for Innovation and Creativity – UCLA, 2013
Fellow of the American Mathematical Society 2013
Elected American Academy of Arts and Sciences, 2010
Elected Fellow of the Society for Industrial and Applied Mathematics, 2010

Paper Awards:

Bertozzi & Flenner's paper "Diffuse Interface Models on Graphs for Classification of High Dimensional Data," which appeared in Multiscale Modeling and Simulation (MMS), was selected as one of the three winning papers of the 2014 SIAM Outstanding Paper Prizes

National press coverage for AFOSR-supported papers:

Van Gennip, Y., B. Hunter, R. Ahn, P. Elliott, K. Luhz, M. Halvorson, S. Reid, M. Valasik, J. Wo, G. E. Tita, A.L. Bertozzi , P.J. Brantingham. Community detection using spectral clustering on sparse geosocial data. SIAM Journal of Applied Math, 73(1): 67-83, 2013.

Stomakhin, Alexey., Martin B. Short, and Andrea L. Bertozzi, Reconstruction of Missing Data in Social Networks Based on Temporal Patterns of Interactions, *Inverse Problems* 27: 115013, 2011. doi:10.1088/0266-5611/27/11/115013

Ronald Breiger, University of Arizona Sociology (co-PI)

Ronald Breiger, Chair, Section on Mathematical Sociology, American Sociological Association (2009-10)

Yuhan Chang, ISI (co-PI)

Maheswaran, R.; Chang, Y.; Hollingsworth, N.; Levy, T.; Wexler, A.; and Kwok, Sheldon. Alpha Award (Best Research) at the MIT Sloan Sports Analytics Conference, March 2014.

Chang, Y., and Maheswaran, R. The Social Ultimatum Game. Best Demonstration Award, Autonomous Agents and Multi-Agent Systems. 2011.

Maheswaran, R., Chang, Y., Danesis, S., and Henehan, A. Best Research Paper at the 6th Annual MIT Sports Analytics Conference (2012) for "Deconstructing the Rebound with Optical Tracking Data."

Aram Galstyan, ISI (co-PI)

Greg Ver Steeg and Aram Galstyan: Best paper runner up at the 27th Conference on Uncertainty in Artificial Intelligence (UAI 2011), for the paper "A Sequence of Relaxations Constraining Hidden Variable Models".

Kristina Lerman, ISI (co-PI)

Hodas, N.; Kooti, F.; and Lerman, K. Honorable mention paper at the Proceedings of the 7Th International AAAI Conference On Weblogs And Social Media, 2013.

Kang, J.; Lerman, K.; and Getoor, L. Terry Lyons Memorial Award for Best Student Paper at the International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction 2013.

Alexander Tartakovsky, USC Mathematics

Institute of Mathematical Statistics Fellow in 2012

George Tita, UC Irvine Criminology, Law and Society

National and Scientific press coverage for AFOSR-supported papers:

Mohler, George O., Martin B. Short, Sean Malinowski, Mark Johnson, George E. Tita, Andrea L. Bertozzi, and P. Jeffrey Brantingham. Randomized controlled field trials of predictive policing. *Journal of the American Statistical Association*, in press, 2015.

Van Gennip, Y., B. Hunter, R. Ahn, P. Elliott, K. Luhz, M. Halvorson, S. Reid, M. Valasik, J. Wo, G. E. Tita, A.L. Bertozzi , P.J. Brantingham. Community detection using spectral clustering on sparse geosocial data. SIAM Journal of Applied Math, 73(1): 67-83, 2013.

P.J. Brantingham, G.E. Tita, M.B. Short and S. Reid, The Ecology of Gang Territorial Boundaries, *Criminology*, 30:851-885 2012. doi: 10.1111/j.1745-9125.2012.00281.x

Mohler, G.O., M.B. Short, P.J. Brantingham, F.P. Schoenberg, and G.E. Tita, Self-exciting point process modeling of crime. Journal of the American Statistical Association 106(493):100-108, 2011. doi:10.1198/jasa.2011.ap09546.

Postdoctoral and Student Awards

Cristina Garcia-Cardona (Claremont) received Best Student Paper Award in the area of Theory & Methods for “Multiclass diffuse interface models for semi-supervised learning on graphs.” 2nd International Conference on Pattern Recognition Applications and Methods, Barcelona, Spain, February 2013.

Anna Ma (Claremont) received an Outstanding Presentation Award for “Linking Social Media to Crime and Disorder.” MAA Undergraduate Poster Session at 2014 Joint Mathematics Meetings, Baltimore, MD, January 2014.

Eric Schoon (UofA), National Science Foundation (NSF) Graduate Research Fellowship (3-year award)

Eric Schoon (UofA) was awarded the Elise Boulding Graduate Paper Award for 2014. This award is bestowed by the American Sociological Association, Section on Peace, War, and Social Conflict. The award is for Eric's paper, "The Asymmetry of Legitimacy: Analyzing the Legitimation of Violence in 30 Cases of Insurgent Revolution," which has been presented at the U of Arizona workshop for graduate students working on the AFOSR-MURI grant and at MURI project meetings, and has (May 2014) received a “conditional accept” from the journal *Social Forces*. The paper is closely related to Eric's dissertation research.

Greg Ver Steeg (ISI) was awarded an AFOSR Young Investigator Award, 2012.

V. Papers Published or In Press:

1 Allahverdyan, A.E., and Galstyan, A., "Opinion Dynamics with Confirmation Bias", *PLoS ONE*, 9(7):e99557. 07 2014.

2 Bakker, René M., Jörg Raab, and H. Brinton Milward. A preliminary theory of dark network resilience. *Journal of Policy Analysis and Management*. 31(1): 33-62, 2012.

3 Banerjee, T., V. V. Veeravalli, and A.G. Tartakovsky, Decentralized Data-Efficient Quickest Change Detection, *Proceedings of the IEEE International Symposium on Information Theory (ISIT 2013),* Istanbul, Turkey, July 97-12, pp. 2587-2591, 2013.

4 Bertozzi, Andrea L., and Arjuna Flenner, Diffuse interface models on graphs for classification of high dimensional data. *Multiscale Modeling and Simulation*, Multiscale Modeling and Simulation, 10:1090-1118, 2012.

5 Bora, N.; Chang, Y.; and Maheswaran, R. "Mobility Patterns and User Dynamics in Racially Segregated Geographies of US Cities." International Conference on Social Computing, Behavioral Modeling and Prediction, 2014.

6 Bora, N.; Zaytsev, V.; Chang, Y.; and Maheswaran, R. "Gang Networks, Neighborhoods and Holidays: Spatiotemporal Patterns in Social Media." ASE/IEEE International Conference on Social Computing (SocialCom), 2013.

7 Bradonjić, Milan, Aric Hagberg, Nicolas Hengartner, Allon G. Percus. "Component evolution in general random intersection graphs." In *Algorithms and Models for the Web-Graph*, edited by R. Kumar and D. Sivakumar. Vol. 6516, pp. 36-49, Berlin: Springer Verlag, 2010.

8 Brantingham, P.J. Prey Selection Among Los Angeles Car Thieves. *Crime Science* 2:3, 2013.

9 Breiger, R.L., E. Schoon, D. Melamed, V. Asal, R.K. Rethemeyer. 2014. "Comparative configurational analysis as a two-mode network problem: A study of terrorist group engagement in the drug trade." Social Networks 36: 23-39, 2014.

10 Carter, S., M. McBride "Experienced Utility versus Decision Utility: Putting the 'S' in Satisfaction," *Journal of Socio-Economics* 42: 13-23, 2013.

11 Chang, Y.; Levinboim, T.; Rajan, V.; and Maheswaran, R. Learning and Evaluating Human-Like NPC Behaviors in Dynamic Games. In Proceedings of the Seventh Artificial Intelligence and Interactive Digital Entertainment (AIIDE) Conference, 2011.

12 Cho, Y. S., Ver Steeg, G., and Galstyan, A. 2013 "Socially Relevant Venue Clustering from Check-in Data," In 11th *Workshop on Mining and Learning with Graphs, MLG, 2013*.

13 Cho, Y.S., A. Galstyan, J. Brantingham, and G. Tita, Generative Models for Spatial-Temporal Processes with Applications to Predictive Criminology, 9th Bayesian Modeling Applications Workshop at UAI'12, Catalina Island, CA, USA, 2012.

14 Cho, Y.S., A. Galstyan, J. Brantingham, and G. Tita, Latent Self-Exciting Point Process Model for Spatial-temporal Networks. *Discrete and Continuous Dynamical Systems* 19(5): 1335-1354, 2014.

15 Cho, Yoon Sik, Greg Ver Steeg, and Aram Galstyan, "Co-evolution of Selection and Influence in Social Networks," In *Proc. of the Twenty-Fifth Conference on Artificial Intelligence*, 2011. arXiv:1106.2788, 2011.

16 Cucuringu, M. Sync-Rank: Robust Ranking, Constrained Ranking and Rank Aggregation via Eigenvector and SDP Synchronization, accepted in IEEE Transactions on Network Science and Engineering, 2015.
17 Cucuringu, M., Synchronization over Z2 and Community Detection in Bipartite Multiplex Networks with Constraints, accepted in *J. Complex Networks*, 2014.
18 D'Orsogna, M., R. Kendall, M. McBride, M. Short. "Criminal Defectors Lead to the Emergence of Cooperation in an Experimental, Adversarial Game," *PLOS ONE* 8 e61458, 2013.
19 Dabkowski, Matthew, Ronald Breiger, and Ferenc Szidarovszky, "Simultaneous-Direct Blockmodeling for Multiple Relations in Pajek." Social Networks 40: 1-16, 2015.
20 Dykhuis, N., P. R. Cohen, Y. Chang, 2013, "Simulating Team Formation in Social Networks." in Proceedings of the *IEEE International Conference on Social Computing* (SocialCom), 2013.
21 Fellouris, G., and A. G. Tartakovsky, Nearly Minimax One-Sided Mixture-Based Sequential Tests, Sequential Analysis, 31(3): 297–325, 2012.
22 Fellouris, G., and A. Tartakovsky, Unstructured Sequential Testing in Sensor Networks, *Proceedings of the 52nd IEEE Conference on Decision and Control*, Florence, Italy, December 10-13, pp. 4784-4789, 2013a.
23 Fellouris, G., and A.G. Tartakovsky, Almost Minimax Sequential Tests of Composite Hypotheses, *Statistica Sinica*, Vol. 23, no. 4, pp. 1717-1741, 2013b.
24 Fonoberova, M., V.A. Fonoberov, and I. Mezic. Global Sensitivity/Uncertainty Analysis for Agent-Based Models. *Reliability Engineering and System Safety*, 118: 8–17, 2013.
25 Fonoberova, M., V.A. Fonoberov, I. Mezic, J. Mezic and P.J. Brantingham. "Nonlinear Dynamics of Crime and Violence in Urban Settings." Journal of Artificial Societies and Social Simulation 15 (1) 2, 2012.
26 Frazier, S., Chang, Y., and Maheswaran, R. Team It: Location-based Network Gaming in Real and Virtual Environments. In the P*roceedings of the International Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE)*, 2012.
27 Garcia-Cardona, Cristina, Arjuna Flenner, Allon G. Percus. "Multiclass diffuse interface models for semi-supervised learning on graphs." Proceedings of the Second International Conference on Pattern Recognition Applications and Methods (ICPRAM 2013), 78-86, 2013.
28 Garcia-Cardona, Cristina, Arjuna Flenner, Allon G. Percus. "Multiclass semi-supervised learning on graphs using Ginzburg-Landau functional minimization." In *Pattern Recognition Applications and Methods*, Advances in Intelligent Systems and Computing, edited by A. Fred and M. De Marsico. Vol. 318, pp. 119-135, Berlin: Springer, 2014.
29 Garcia-Cardona, Cristina, Ekaterina Merkurjev, Andrea L. Bertozzi, Arjuna Flenner, Allon G. Percus. Multiclass data segmentation using diffuse interface methods on graphs. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 36:1600-1613, 2014.
30 Ghosh, R. and Lerman, K. "Rethinking Centrality: The Role of Dynamical Processes in Social Network Analysis." *Discrete and Continuous Dynamical* Systems Series B 19(5):1355-1372, 2014.
31 Ghosh, R., and Lerman, K. A Framework for Quantitative Analysis of Cascades on Networks. In *Proceedings of Web Search and Data Mining Conference* (WSDM), February, 2011.

32 Ghosh, R.; and Lerman, K. The Impact of Network Flows on Community Formation in Models of Opinion Dynamics. Journal of Mathematical Sociology, 39:109--124. 2015.

33 Ghosh, R.; Lerman, K.; Teng, S.; and Yan, X. The Interplay Between Dynamics and Networks: Centrality, Communities, and Cheeger Inequality In Proceedings of the 20th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD'2014), 2014.

34 Gupta, S.; Yan, X.; and Lerman, K. Structural Properties of Ego Networks. In International Conference on Social Computing, Behavioral Modeling and Prediction, April 2015.

35 Hegemann, R. A., L. M. Smith, A. Barbaro, A. L. Bertozzi, S. Reid, and G. E. Tita, Geographical influences of an emerging network of gang rivalries, Physica A, 390 (21-22):3894-3914, 2011.

36 Hegemann, Rachel A., Erik A. Lewis, and Andrea L. Bertozzi, An "Estimate & Score Algorithm" for simultaneous parameter estimation and reconstruction of missing data on social networks. *Security Informatics*, 2:1, 2013.

37 Hodas, N and Lerman, K. How Limited Visibility and Divided Attention Constrain Social Contagion. In *ASE/IEEE International Conference on Social Computing,* 2012.

38 Hodas, N. O.; and Lerman, K. "The Simple Rules of Social Contagion." *Scientific Reports* 4, 2014.

39 Hodas, N.; Kooti, F.; and Lerman, K. "Friendship Paradox Redux: Your Friends Are More Interesting Than You." In *Proceedings of the 7Th International AAAI Conference On Weblogs And Social Media (ICWSM)*, 2013. Honorable mention paper.

40 Hogg, T., and Lerman, K. Social Dynamics of Digg. *EPJ Data Science*, 1(5):, June, 2012.

41 Hogg, T.; Lerman, K.; and Smith, L. M. "Stochastic Models Predict User Behavior in Social Media." *ASE Human*, 2(1), 2013.

42 Hu, H.Y., Thomas Laurent, Mason A. Porter, Andrea L. Bertozzi, A Method Based on Total Variation for Network Modularity Optimization using the MBO Scheme. *SIAM J. Appl. Math.,* 73(6), pp. 2224-2246, 2013.

43 Intagorn, S.; and Lerman, K. Placing User-generated Content on the Map with Confidence. In ACM GIS, 2014.

44 Juul, J., A. Kianercy, S. Bernhardsson and S. Pigolotti. "Replicator dynamics with turnover of players" Phys. Rev. E 88, 022806, 2013.

45 Kang, J.; and Lerman, K VIP: Incorporating Human Cognitive Biases in a Probabilistic Model of Retweeting. In *International Conference on Social Computing, Behavioral Modeling and Prediction*, April 2015a.

46 Kang, J.; and Lerman, K. "LA-CTR: A Limited Attention Collaborative Topic Regression for Social Media." In *Twenty-Seventh AAAI Conference on Artificial Intelligence (AAAI)*, 2013a.

47 Kang, J.; and Lerman, K. User Effort and Network Structure Mediate Access to Information in Networks. In Proceedings of the 9th International AAAI Conference on Weblogs and Social Media (ICWSM), 2015b.

48 Kang, J.; and Lerman, K."Structural and Cognitive Bottlenecks to Information Access in Social Networks." In *Proceedings of 24th ACM Conference on Hypertext and Social Media*, 2013b.

49 Kang, J.; Lerman, K.; and Getoor, L. “LA-LDA: A Limited Attention Model for Social Recommendation.” In *International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction (SBP)*, 2013c. Terry Lyons Memorial Award for Best Student Paper.

50 Kang, Jeon-hyung, and Kristina Lerman. Factors Affecting Access to Information in Social Networks, in revision, *ACM Transactions on the Web, 2015c.*

51 Kianercy, A., and A. Galstyan. Coevolutionary networks of reinforcement-learning agents. Physical Review E 88, 012815, doi: 10.1103/PhysRevE.88.012815, 2013.

52 Kianercy, A., and Galstyan, A. Dynamics of Boltzman Q Learning in Two-Player Two-Action Games. Physical Review E. 85, 041145, 2012.

53 Kianercy, A., Galstyan, A. Allahverdyan, A. Adaptive Agents on Evolving Networks. In Proc. of AAMAS, 2012.

54 Kim, E., Chang, Y., Graham, J., Iyer, R. and Maheswaran, R. Moral Values from Simple Game Play. International Conference on Social Computing, Behavioral-Cultural Modeling, & Prediction (SBP), 2012.

55 Kim, E.; Chang, Y.; Maheswaran, R; Chi, L.; Ning, Y. Negotiation and Adaptation in Network Games. In the *Fifth International Workshop on Agent-based Complex Automated Negotiations (ACAN)*, 2012.

56 Kim, E.; Chi, L.; Maheswaran, R.; and Chang, Y. Dynamics of Social Interactions in a Network Game. In *Proceedings of the Third IEEE International Conference on Social Computing (SocialCom)*, 2011.

57 Kim, E.; Chi, L.; Ning, Y.; Chang, Y.; and Maheswaran, R. Adaptive Negotiating Agents in Dynamic Games: Outperforming Human Behavior in Diverse Societies. In *Proceedings of the International Conference on Autonomous Agents and Multi-Agents Systems (AAMAS),* 2012.

58 Kooti, F., Hodas, N. and Lerman, K. “Network Weirdness: Exploring the Origins of Network Paradoxes” in *Proc. International Conference of Weblogs and Social Media (ICWSM)*, 2014.

59 Kooti, F.; Aiello, L. M.; Grbovic, M.; Lerman, K.; and Mantrach, A. Evolution of Conversations in the Age of Email Overload. In Proceedings of 24th International World Wide Web Conference (WWW), 2015.

60 Kooti, Farshad, Kristina Lerman, Luca M. Aiello, Mihajlo Grbovic, Nemanja Djuric, and Vladan Radosavljevic. “Portrait of an Online Shopper: Understanding and Predicting Consumer Behavior”, accepted in *International Conference on Web Search and Data Mining* (WSDM), 2015.

61 Kostić, T. and A. Bertozzi. "Statistical Density Estimation Using Threshold Dynamics for Geometric Motion." *Journal of Scientific Computing* 54(2-3): 513-530, 2013.

62 Lee, S. H., M. Cucuringu, M. A. Porter, "Density-Based and Transport-Based Core-Periphery Structures in Networks", Physical Review E, 89(3): 032810, 2014.

63 Lerman, K., Hogg, T. Leveraging Position Bias to Improve Peer Recommendation. *PLoS ONE* 9(6): e98914, 2014.

64 Lerman, K. and Ghosh, R. Network Structure, Topology and Dynamics in Generalized Models of Synchronization. *Phys. Rev. E* 86, 2012.

65 Lerman,K. Intagorn, S., Kang, JH, and Ghosh, R. Using Proximity to Predict Activity in Social Networks. In Proc. of World Wide Web Conference, 2012.

66 Lerman, K.; Jain, P.; Ghosh, R.; Kang, J.; and Kumaraguru, P. “Limited Attention and Centrality in Social Networks.”In *Proceedings of International Conference on Social Intelligence and Technology (SOCIETY)*, 2013.
67 Lerman, Kristina, Xioran Yan and Xin-zeng Wu. The Majority Illusion in Social Networks, in revision, *Plos One*, 2015.
68 Lewis, E., G. Mohler, P.J. Brantingham, A. Bertozzi, Self-Exciting Point Process Models of Civilian Deaths in Iraq, *Security Journal*, 25:244-264, 2011.
69 Li, Z.; Chang, Y.; Maheswaran, R. “Graph Formation Effects on Social Welfare and Inequality in a Networked Resource Game.” International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction, 2013.
70 Ma, Anna, Arjuna Flenner, Deanna Needell, Allon G. Percus, “Improving image clustering using sparse text and the wisdom of the crowds,” Proceedings of the 48th Annual Asilomar Conference on Signals, Systems, and Computers, in press 2015.
71 Ma, Anna, Deanna Needell, Aaditya Ramdas, “Convergence properties of the randomized extended Gauss-Seidel and Kaczmarz methods,” SIAM Journal on Matrix Analysis and Applications, in press, 2015.
72 McBride, M. "Authority in Mormonism: A Rational Choice Analysis," in P. Mason, ed., *Mormon Studies in the 21st Century*, University of Utah Press, forthcoming 2015a.
73 McBride, M., “Why Churches Need Free-riders,” Journal of Behavioral and Experimental Economics, 58: 77-87, 2015b.
74 McBride, M., D. Hewitt, “The Enemy You Can't See: An Investigation of the Disruption of Dark Networks,” *Journal of Economic Behavior and Organization* 93: 32-50, 2013
75 McBride, M., M. Caldara, The Efficacy of Tables versus Graphs in Disrupting Dark Networks: An Experimental Study, *Social Networks* 35: 406-422, 2013.
76 McBride, M., S. Skaperdas, "Conflict, Settlement, and the Shadow of the Future," *Journal of Economic Behavior and Organization* 105: 75-89, 2014
77 McCalla, S.G., P.J. Brantingham, and M.B. Short. The effects of sacred value networks within an evolutionary, adversarial game. *Journal of Statistical Physics* 151(3-4): 673-688, 2013.
78 Melamed, D., R.L. Breiger, and A.J. West, “Community Structure in Multi-Mode Networks: Applying an Eigenspectrum Approach.” Connections 33: 18-23, 2013.
79 Merkurjev, E., T. Kostic, and A. L. Bertozzi. An MBO Scheme on Graphs for Segmentation and Image Processing. *SIAM J. Imaging Sci.* 6(4), 1903-1930, 2013.
80 Merkurjev, Ekaterina, Cristina Garcia-Cardona, Andrea L. Bertozzi, Arjuna Flenner, Allon G. Percus. “Diffuse interface methods for multiclass segmentation of high-dimensional data,” *Applied Mathematics Letters*, 33, 29-34, 2014.
81 Milward, H. Brinton, “What Healthcare Leaders Can Learn About Research on Dark Networks.” Healthcare Management Forum. Fall 2015.
82 Mohler, G.O., M. B. Short, S. Malinowski, M. Johnson, G. E. Tita, A.L. Bertozzi and P. J. Brantingham. Randomized Controlled Field Trials of Predictive Policing. *Journal of the American Statistical Association*, 2015. published online Oct 7, 2015.
83 Mohler, G.O., M.B. Short, P.J. Brantingham, F.P. Schoenberg, and G.E. Tita, Self-exciting point process modeling of crime. *Journal of the American Statistical Association* 106(493):100-108, 2011.

84 Narang, K., K. Lerman and P. Kumaraguru “Network Flows and the Link Prediction Problem” The 7th SNA-KDD Workshop ’13 (SNA-KDD’13), August 11, 2013, Chicago, 2013.
85 Ni, B.; Chang, Y.; Maheswaran, R. “Social Welfare and Inequality in a Networked Resource Game with Human Players.” ASE/IEEE International Conference on Social Computing (SocialCom), 2013.
86 Polunchenko, A.S., and A.G. Tartakovsky, State-of-the-Art in Sequential Change-Point Detection, Methodology and Computing in Applied Probability, 14(3): 649–684, 2012.
87 Polunchenko, A.S., G. Sokolov, and A.G. Tartakovsky, “Optimal Design and Analysis of the Exponentially Weighted Moving Average Chart for Exponential Data.” Sri Lankan Journal of Applied Statistics 5(4):57-80, 2014.
88 Popp, J.K., H.B. Milward, G. MacKean, A.Casebeer, and R. Lindstrom, “Interorganizational Networks: A Review of the Literature to Inform Practice” IBM Center for the Business of Government. September, 2014.
89 Purcell, Christopher and Puck Rombach. On the Complexity of Role Colouring Planar Graphs, Trees and Cographs. 2015. *Journal of Discrete Algorithms*, in press, 2015.
90 Raghavan, V., A. Galstyan, and A.G. Tartakovsky, Hidden Markov Models for the Activity Profile of Terrorist Groups, *Annals of Applied Statistics*, vol. 7, no. 4, pp. 2402-2430, 2013.
91 Raghavan, V., G. V. Steeg, A. Galstyan, and A.G. Tartakovsky, Modeling Temporal Activity Patterns in Dynamic Social Networks, *IEEE Transactions on Control Systems Technology*, in press 2014.
92 Ridinger, G. and M. McBride. Money Affects Theory of Mind Differently by Gender. PLOS One 10(12): e0143973, 2015
93 Ridinger, G., R. John, M. McBride, N. Scurich, "Attacker Deterrence and Perceived Risk in a Stackelberg Security Game," *Risk Analysis*, in press 2015.
94 Schoon, Eric W. "The Paradox of Legitimacy: Resilience, Successes, and the Multiple Identities of the Kurdistan Workers' Party in Turkey". *Social Problems* 62(2), 266-285, 2015.
95 Schoon, Eric W. "The Asymmetry of Legitimacy: Analyzing the Legitimation of Violence in 30 Cases of Insurgent Revolution." *Social Forces* 93(2): 779-801, 2014.
96 Short, M.B., G.O. Mohler, P.J. Brantingham, and G.E. Tita, Gang Rivalry Dynamics Via Couple Point Process Networks, *Discrete and Continuous Dynamical Systems* 19(5): 1459-1477, 2014.
97 Short, M.B., P.J. Brantingham, and M.R. D'Orsogna. Cooperation and punishment in an adversarial game: How defectors pave the way to peaceful society. *Physical Review E* 82:66114-1-7, 2010.
98 Smith, Laura M., Kristina Lerman, Cristina Garcia-Cardona, Allon G. Percus, Rumi Ghosh. “Spectral clustering with epidemic diffusion,” Physical Review E, 88, 042813, 2013.
99 Smith, L. M.; Zhu, L.; Lerman, K.; and Kozareva, Z, "The Role of Social Media in the Discussion of Controversial Topics.” In ASE/IEEE International Conference on Social Computing, 2013.
100 Smith, Laura M., Andrea L. Bertozzi, P. Jeffrey Brantingham, George E. Tita, and Matthew Valasik, Adaptation of an Ecological Territorial Model to Street Gang Spatial Patterns in Los Angeles, *Discrete and Continuous Dynamical Systems* 39(2): 3223-3244,

2012.

101 Smith, Laura M., Linhong Zhu, Kristina Lerman and Allon G. Percus. Partitioning Networks with Node Attributes by Compressing Information Flow, in revision. *ACM Transactions on Knowledge Discovery from Data*, 2015.
102 Stomakhin, Alexey., Martin B. Short, and Andrea L. Bertozzi, Reconstruction of Missing Data in Social Networks Based on Temporal Patterns of Interactions, *Inverse Problems* 27: 115013, 2011.
103 Tartakovsky, A.G., and M. Pollak, Nearly Minimax Changepoint Detection Procedures. In *Proceedings of the IEEE International Symposium on Information Theory*, St. Petersburg, Russia, July 31-August 5, 2011.
104 Tartakovsky, A.G., I. Nikoforov, and M. Basseville, Sequential Analysis: Hypothesis Testing and Change-Point Detection, Chapman & Hall/CRC, 2015.
105 Tartakovsky, A.G., M. Pollak, and A.S. Polunchenko, Third-order Asymptotic Optimality of the Generalized Shiryaev–Roberts Detection Procedures, Theory of Probability and Its Applications, 56(3): 457–484, 2012.
106 Tartakovsky, A.G., Nearly Optimal Sequential Tests of Composite Hypotheses – Revisited, *Proceedings of the Steklov Institute of Mathematics* 287(1):268-288, 2015.
107 Van Gennip, Y., B. Hunter, R. Ahn, P. Elliott, K. Luhz, M. Halvorson, S. Reid, M. Valasik, J. Wo, G. E. Tita, A.L. Bertozzi , P.J. Brantingham. Community detection using spectral clustering on sparse geosocial data. SIAM Journal of Applied Math, 73(1): 67-83, 2013.
108 Van Gennip, Y., Nestor Guillen, Braxton Osting, and Andrea L. Bertozzi, Mean curvature, threshold dynamics, and phase field theory on finite graphs, *Milan J. of Math*, 82(1):3-65, 2014.
109 Van Gennip, Yves, and Andrea L. Bertozzi. Gamma-convergence of graph Ginzburg-Landau Functionals. *Advances in Differential Equations*, 17:1115-1180, 2012.
110 Ver Steeg, G, and A. Galstyan. 2012. Information Transfer in Social Media, In Proc. of International Conference on World Wide Web, 2012.
111 Ver Steeg, G. , A. Galstyan, and A. E.Allahverdyan, Statistical mechanics of semi-supervised clustering in sparse graphs. Journal of Statistical Mechanics: Theory and Experiment 2011 (08):P08009, 2011.
112 Ver Steeg, G. and A. Galstyan. Information-Theoretic Measure of Influence based on Content Dynamics, in Proc. of the 6th ACM Conference on Web Search and Data Mining, WSDM'13, Rome Italy, 2013a.
113 Ver Steeg, G., A. Galstyan, F. Sha, S. DeDeo. Demystifying Information-Theoretic Clustering, in Proc. of ICML'14, 2014.
114 Ver Steeg, G., and A. Galstyan, "A Sequence of Relaxations Constraining Hidden Variable Models", In Proc. of the Twenty-Seventh Conference on Uncertainty in Artificial Intelligence, 2011.
115 Ver Steeg, G., and A. Galstyan. Statistical Tests for Contagion in Observational Social Network Studies, in Proc. of AISTATS'13, 2013b.
116 Ver Steeg, G., and Ghosh, R. and Lerman, K, "What stops social epidemics?", In Proc. of International Conference on Weblogs and Social Media, 2011.

117 Ver Steeg, G., Moore, C., Galstyan, A, Allahverdyan A. Phase Transitions in Community Detection: A Solvable Toy Model, EuroPhysics Letters 106, 48004, 2014.

118 Von Brecht, J. Benjamin Sudakov, and A. L. Bertozzi, Swarming on Random Graphs II, *J. Stat. Phys.*, 158(3):699-734, 2015.

119 Von Brecht, J., T. Kolokolnikov, A.L. Bertozzi, H. Sun. Swarming on random graphs. *Journal of Statistical Physics*, 151(1-2):150-173, 2013.

120 Walsh, T.J., J. Taheri, J.B. Wright, P.R. Cohen. 2011. Leadership Games and their Application in Super-Peer Networks. *Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence,* San Francisco, Aug 7-11, 2011.

121 Woodworth, J. T., G. O. Mohler, A. L. Bertozzi and P. J. Brantingham, Nonlocal Crime Density Estimation Incorporating Housing Information, Phil. Trans. Roy. Soc. A, Phil. Trans. Roy. Soc. A, 372(2028), 20130403, 2014.

122 Zhu, L.; and Lerman, K. A Visibility-based Model for Link Prediction in Social Media. In Proceedings of the *ASE/IEEE Conference on Social Computing*, 2014.

123 Zipkin, Joseph R., Frederic P. Schoenberg, Kathryn Coronges, and Andrea L. Bertozzi, Point-process models of social network interactions: parameter estimation and missing data recovery, *EJAM*, in press, 2015.

VI. Submitted Papers

S1 Allahverdyan, A.E. and Galstyan, A., “Active Inference for Binary Symmetric Hidden Markov Models”, submitted to Journal of Statistical Physics, 2015.

S2 Allison, B. “Do Players Prefer to Bargain Noncooperatively in the Shadow of Conflict?” 2014, submitted

S3 Bradonjic, Milan, Aric Hagberg, Nicolas W. Hengartner, Nathan Lemons, Allon G. Percus, “The phase transition in inhomogeneous random intersection graphs,” submitted to Discrete Applied Mathematics.

S4 Caldera, M., M. McBride, M. McCarter, R. Sheremeta, “The Three Pillars of Conflict,” 2014, submitted

S5 Candelo, N., S. Forbes, S. Martin, M. McBride, “Endogenous Formation of Terror Networks: Theory and Experiment,” 2013, submitted.

S6 Cucuringu, M. and J. Woodworth. Point Localization and Density Estimation from Ordinal kNN graphs using Synchronization", submitted, 2015.

S7 Cucuringu, M. and R. Erban. ADM-CLE approach for detecting slow variables in continuous time Markov chains and dynamic data, submitted, 2015.

S8 Cucuringu, M., I. Koutis and S. Chawla, Scalable Constrained Clustering: A Generalized Spectral Method, submitted to AISTATS, 2015.

S9 Cucuringu, M., M. P. Rombach, S. H. Lee, M. A. Porter. Detection of Core-Periphery Structure in Networks Using Spectral Methods and Geodesic Paths, submitted, 2015.

S10 Dykhuis, Nathaniel J., Rossi, Filippo, and Morrison, Clayton T., 2015. “Contributions to Teams Formed in Dynamic Networks.” submitted to The Multi-disciplinary Conference on Reinforcement Learning and Decision Making (RLDM).

S11 Fox, E. W., M. B. Short, F. P. Schoenberg, K. D. Coronges, and A. L. Bertozzi, Modeling e-mail networks and inferring leadership using self-exciting point processes, submitted, 2013.

S12 Gravel, J., Allison, B., West-Fagan, J., McBride, M., & Tita, G. E., “ Birds of a Feather Fight Together: Status-Enhancing Violence, Social Distance and the Emergence of Homogenous Gangs”, 2015, submitted.

S13 Lai, E., D. Moyer, B. Yuan, E. Fox, B. Hunter, A. L. Bertozzi, and P. J. Brantingham, Topic Time Series Analysis of Microblogs, submitted 2014.

S14 McBride, M. "A Rational Choice Theory of Religious Authority," July 2013, submitted

S15 McBride, M., R. Kendall, M. Short, M D’Orsogna. 2014. “Crime, Punishment, and Evolution in an Adversarial Game” submitted.

S16 McBride, M., S. Skaperdas, P. Tsai, "Why Go to Court? Bargaining Failure under the Shadow of Trial with Complete Information," 2014, submitted

S17 Merkurjev, Ekaterina, Andrea Bertozzi, Kristina Lerman and Xioran Yan. “Modified Cheeger and Ratio Cut Methods Using the Ginzburg-Landau Functional for Classification of High-Dimensional Data” submitted to *Journal of Inverse Problems*.

S18 Mohr, R., and I. Mezic. Construction of eigenfunctions for scalar-type operators. submitted to Ergodic Theory and Dynamical Systems, 2014.
S19 Schoon, Eric, and A. Joseph West, 2013. “From Prophecy to Practice: Mutual Selection Cycles in the Routinization of Charismatic Authority.” submitted to *Sociological Theory*.
S20 Smith, Laura M., Linhong Zhu, Kristina Lerman, Allon G. Percus, “Partitioning networks with node attributes by compressing information flow,” submitted to the ACM Transactions on Knowledge Discovery from Data.
S21 Susuki, Y., and I. Mezic. Ergodic partition and invariant sets of quasiperiodically forced dynamical systems, submitted to *Chaos*, 2014.

VII. Students Supported:

POSTDOCS AND PHD STUDENTS (CUMULATIVE)

Count	First Name	Last Name	MURI Institution
1	Blake	Allison	UC Irvine
2	Mark	Bloxsom	UC Irvine
3	Michael	Caldera	UC Irvine
4	Yoon Sik	Cho	ISI
5	Jacob	Cramer	UofA
6	Mihai	Cucuringu	UCLA
7	Rachel	Danson	UCLA
8	Andrew Paul	Davis	UofA
9	Nathan	Dykhuis	UofA
10	Georgios	Fellouris	USC
11	Jennifer	Flenner	CGU
12	Cristina	Garcia-Cardona	CGU
13	Rumi	Ghosh	ISI
14	Lindsay	Gifford	UCLA
15	Jason	Gravel	UC Irvine
16	Megan	Halvorson	UC Irvine
17	David	Hewitt	UC Irvine
18	Nathan	Hodas	ISI
19	Megan	Holvorsan	UC Irvine
20	Huiyi	Hu	UCLA
21	Blake	Hunter	UCLA
22	Jeon-hyung	Kang	ISI
23	Ardeshir	Kianercy	ISI
24	Eunkyung	Kim	ISI
25	Si-Yuan	Kong	UC Irvine
26	Farshad	Kooti	ISI
27	Sharmila	Kopanathi	CGU
28	Tijana	Kostick	UCLA
29	Lukas	Kroc	CGU
30	John Anthony	Labarga	USC
31	Erik	Lewis	UCLA
32	Heather	Loyd	UCLA
33	Zhiyun	Lu	ISI
34	Anna	Ma	CGU
35	Rajiv	Maheswaran	ISI
36	Scott	McCalla	UCLA

37	David	Melamed	UofA
38	Travis	Meyer	UCLA
39	Sabrina	Nardin	UofA
40	Aleksey	Polunchenko	USC
41	Vasanth	Raghavan	USC
42	Shannon	Reid	UC Irvine
43	Michaela	Rombach	UCLA
44	Filippo	Rossi	UofA
45	Eric	Schoon	UofA
46	Eric	Schoon	UofA
47	Martin	Short	UCLA
48	Laura	Smith	ISI
49	Greg	Sokolov	ISI
50	Benjamin	Sudakov	UCLA
51	Justin	Sunu	CGU
52	Melissa	Tong	ISI
53	Matt	Valasik	UC Irvine
54	Attila	Varga	UofA
55	Greg	Ver Steeg	ISI
56	James	Von Brecht	UCLA
57	Joseph	West	UofA
58	Jenny	West-Fagan	UC Irvine
59	James	Wo	UC Irvine
60	Joseph	Woodward	UCLA
61	Xiaoran	Yan	ISI
62	Linhong	Zhu	ISI
63	Joseph	Zipkin	UCLA

MA/MS STUDENTS (CUMULATIVE)

Count	Fist Name	Last Name	MURI Institution
1	Suchindra	Agarwal	ISI
2	Nibir	Bora	ISI
3	Luyan	Chi	ISI
4	Avinash	Kashyap	ISI
5	Gautam	Koshik	ISI
6	Pratik	Pattani	ISI
7	Pranav	Vaniawala	ISI
8	Ning	Yu	ISI
9	Vladimir	Zaytsev	ISI
10	Alfredo	Carillo	UofA
11	George	Richardson	CGU

UNDERGRADUATE STUDENTS (CUMULATIVE)

Count	Name, MURI Institution
1	Ian Drayer, NSF REU student
2	Kym Louie, NSF REU student
3	Joy Yu, NSF REU student
4	Raymond Ahn, NSF REU student
5	Peter Elliot, NSF REU student
6	Kyle Luh, NSF REU student
7	Emmanuel Tsukerman, UCLA IPAM RIPS Summer Student
8	Olivier Mercier, UCLA IPAM RIPS Summer Student
9	Perla Salazar, UCLA IPAM RIPS Summer Student
10	Daniel Vazquez, UCLA IPAM RIPS Summer Student
11	Alexander Newman, ISI
12	Jerry Luo, UCLA
13	Juhyun Kim, UCLA

DOD AND LAW ENFORCEMENT CONTACTS

Arjuna Flenner (China Lake)
LTC Clark Frederick (JSOC)
Commander Sean Malinowski (LAPD)
Laurie Fenstermacher (AFRL)
Jennifer Lopez (AFRL)

1.

1. Report Type

Final Report

Primary Contact E-mail
Contact email if there is a problem with the report.

branting@ucla.edu

Primary Contact Phone Number
Contact phone number if there is a problem with the report

4242987732

Organization / Institution name

UCLA Anthropology

Grant/Contract Title
The full title of the funded effort.

Inferring Structure and Forecasting Dynamics on Evolving Networks

Grant/Contract Number
AFOSR assigned control number. It must begin with "FA9550" or "F49620" or "FA2386".

FA9550-10-1-0569

Principal Investigator Name
The full name of the principal investigator on the grant or contract.

P. Jeffrey Brantigham

Program Manager
The AFOSR Program Manager currently assigned to the award

Benjamin A. Knott

Reporting Period Start Date

09/30/2010

Reporting Period End Date

09/29/2015

Abstract

Networks lie at the heart of social organization and are central to the emergence and perpetuation of adversarial threats. Complex interactions between evolving network topologies and dynamic socio-cultural processes present immense challenges for countering such threats. This interdisciplinary MURI was positioned at the interface between social, mathematical and computational approaches to networks with goals of developing (1) stable metrics for inferring network structures, (2) forecasting dynamical social and information processes on networks, and (3) predicting the outcomes of network interventions. Major progress was made in measuring and modeling spatio-temporal event patterning in relation to network structures, event inference on networks, community detection and classification, processes of network formation, information spread and dynamical games on graphs, and experimental manipulation of social networks in laboratory settings. The MURI was grounded in empirical data on human activity patterns, crime event patterning, social media processes and observations collected through controlled laboratory and online experimental platforms.

Distribution Statement
This is block 12 on the SF298 form.

Distribution A - Approved for Public Release

Explanation for Distribution Statement

If this is not approved for public release, please provide a short explanation. E.g., contains proprietary information.

SF298 Form

Please attach your SF298 form. A blank SF298 can be found here. Please do not password protect or secure the PDF The maximum file size for an SF298 is 50MB.

AFD-070820-035-PJB-Completed-12-14-15.pdf

Upload the Report Document. File must be a PDF. Please do not password protect or secure the PDF . The maximum file size for the Report Document is 50MB.

AFOSR_MURI_Final_Performance_Report_12_12_15.pdf

Upload a Report Document, if any. The maximum file size for the Report Document is 50MB.

Archival Publications (published) during reporting period:

1 Allahverdyan, A.E., and Galstyan, A., "Opinion Dynamics with Confirmation Bias", PLoS ONE, 9(7):e99557. 07 2014.
2 Bakker, René M., Jörg Raab, and H. Brinton Milward. A preliminary theory of dark network resilience. Journal of Policy Analysis and Management. 31(1): 33-62, 2012.
3 Banerjee, T., V. V. Veeravalli, and A.G. Tartakovsky, Decentralized Data-Efficient Quickest Change Detection, Proceedings of the IEEE International Symposium on Information Theory (ISIT 2013), Istanbul, Turkey, July 97-12, pp. 2587-2591, 2013.
4 Bertozzi, Andrea L., and Arjuna Flenner, Diffuse interface models on graphs for classification of high dimensional data. Multiscale Modeling and Simulation, Multiscale Modeling and Simulation, 10:1090-1118, 2012.
5 Bora, N.; Chang, Y.; and Maheswaran, R. "Mobility Patterns and User Dynamics in Racially Segregated Geographies of US Cities." International Conference on Social Computing, Behavioral Modeling and Prediction, 2014.
6 Bora, N.; Zaytsev, V.; Chang, Y.; and Maheswaran, R. "Gang Networks, Neighborhoods and Holidays: Spatiotemporal Patterns in Social Media." ASE/IEEE International Conference on Social Computing (SocialCom), 2013.
7 Bradonjić, Milan, Aric Hagberg, Nicolas Hengartner, Allon G. Percus. "Component evolution in general random intersection graphs." In Algorithms and Models for the Web-Graph, edited by R. Kumar and D. Sivakumar. Vol. 6516, pp. 36-49, Berlin: Springer Verlag, 2010.
8 Brantingham, P.J. Prey Selection Among Los Angeles Car Thieves. Crime Science 2:3, 2013.
9 Breiger, R.L., E. Schoon, D. Melamed, V. Asal, R.K. Rethemeyer. 2014. "Comparative configurational analysis as a two-mode network problem: A study of terrorist group engagement in the drug trade." Social Networks 36: 23-39, 2014.
10 Carter, S., M. McBride "Experienced Utility versus Decision Utility: Putting the 'S' in Satisfaction," Journal of Socio-Economics 42: 13-23, 2013.
11 Chang, Y.; Levinboim, T.; Rajan, V.; and Maheswaran, R. Learning and Evaluating Human-Like NPC Behaviors in Dynamic Games. In Proceedings of the Seventh Artificial Intelligence and Interactive Digital Entertainment (AIIDE) Conference, 2011.
12 Cho, Y. S., Ver Steeg, G., and Galstyan, A. 2013 "Socially Relevant Venue Clustering from Check-in Data," In 11th Workshop on Mining and Learning with Graphs, MLG, 2013.
13 Cho, Y.S., A. Galstyan, J. Brantingham, and G. Tita, Generative Models for Spatial-Temporal Processes with Applications to Predictive Criminology, 9th Bayesian Modeling Applications Workshop at UAI'12, Catalina Island, CA, USA, 2012.
14 Cho, Y.S., A. Galstyan, J. Brantingham, and G. Tita, Latent Self-Exciting Point Process Model for Spatial-temporal Networks. Discrete and Continuous Dynamical Systems 19(5): 1335-1354, 2014.
15 Cho, Yoon Sik, Greg Ver Steeg, and Aram Galstyan, "Co-evolution of Selection and Influence in Social Networks," In Proc. of the Twenty-Fifth Conference on Artificial Intelligence, 2011. arXiv:1106.2788, 2011.
16 Cucuringu, M. Sync-Rank: Robust Ranking, Constrained Ranking and Rank Aggregation via Eigenvector and SDP Synchronization, accepted in IEEE Transactions on Network Science and Engineering, 2015.

17 Cucuringu, M., Synchronization over Z2 and Community Detection in Bipartite Multiplex Networks with Constraints, accepted in J. Complex Networks, 2014.
18 D'Orsogna, M., R. Kendall, M. McBride, M. Short. "Criminal Defectors Lead to the Emergence of Cooperation in an Experimental, Adversarial Game," PLOS ONE 8 e61458, 2013.
19 Dabkowski, Matthew, Ronald Breiger, and Ferenc Szidarovszky, "Simultaneous-Direct Blockmodeling for Multiple Relations in Pajek." Social Networks 40: 1-16, 2015.
20 Dykhuis, N., P. R. Cohen, Y. Chang, 2013, "Simulating Team Formation in Social Networks." in Proceedings of the IEEE International Conference on Social Computing (SocialCom), 2013.
21 Fellouris, G., and A. G. Tartakovsky, Nearly Minimax One-Sided Mixture-Based Sequential Tests, Sequential Analysis, 31(3): 297–325, 2012.
22 Fellouris, G., and A. Tartakovsky, Unstructured Sequential Testing in Sensor Networks, Proceedings of the 52nd IEEE Conference on Decision and Control, Florence, Italy, December 10-13, pp. 4784-4789, 2013a.
23 Fellouris, G., and A.G. Tartakovsky, Almost Minimax Sequential Tests of Composite Hypotheses, Statistica Sinica, Vol. 23, no. 4, pp. 1717-1741, 2013b.
24 Fonoberova, M., V.A. Fonoberov, and I. Mezic. Global Sensitivity/Uncertainty Analysis for Agent-Based Models. Reliability Engineering and System Safety, 118: 8–17, 2013.
25 Fonoberova, M., V.A. Fonoberov, I. Mezic, J. Mezic and P.J. Brantingham. "Nonlinear Dynamics of Crime and Violence in Urban Settings." Journal of Artificial Societies and Social Simulation 15 (1) 2, 2012.
26 Frazier, S., Chang, Y., and Maheswaran, R. Team It: Location-based Network Gaming in Real and Virtual Environments. In the Proceedings of the International Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE), 2012.
27 Garcia-Cardona, Cristina, Arjuna Flenner, Allon G. Percus. "Multiclass diffuse interface models for semi-supervised learning on graphs." Proceedings of the Second International Conference on Pattern Recognition Applications and Methods (ICPRAM 2013), 78-86, 2013.
28 Garcia-Cardona, Cristina, Arjuna Flenner, Allon G. Percus. "Multiclass semi-supervised learning on graphs using Ginzburg-Landau functional minimization." In Pattern Recognition Applications and Methods, Advances in Intelligent Systems and Computing, edited by A. Fred and M. De Marsico. Vol. 318, pp. 119-135, Berlin: Springer, 2014.
29 Garcia-Cardona, Cristina, Ekaterina Merkurjev, Andrea L. Bertozzi, Arjuna Flenner, Allon G. Percus. Multiclass data segmentation using diffuse interface methods on graphs. IEEE Transactions on Pattern Analysis and Machine Intelligence 36:1600-1613, 2014.
30 Ghosh, R. and Lerman, K. "Rethinking Centrality: The Role of Dynamical Processes in Social Network Analysis." Discrete and Continuous Dynamical Systems Series B 19(5):1355-1372, 2014.
31 Ghosh, R., and Lerman, K. A Framework for Quantitative Analysis of Cascades on Networks. In Proceedings of Web Search and Data Mining Conference (WSDM), February, 2011.
32 Ghosh, R.; and Lerman, K. The Impact of Network Flows on Community Formation in Models of Opinion Dynamics. Journal of Mathematical Sociology, 39:109--124. 2015.
33 Ghosh, R.; Lerman, K.; Teng, S.; and Yan, X. The Interplay Between Dynamics and Networks: Centrality, Communities, and Cheeger Inequality In Proceedings of the 20th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD'2014), 2014.
34 Gupta, S.; Yan, X.; and Lerman, K. Structural Properties of Ego Networks. In International Conference on Social Computing, Behavioral Modeling and Prediction, April 2015.
35 Hegemann, R. A., L. M. Smith, A. Barbaro, A. L. Bertozzi, S. Reid, and G. E. Tita, Geographical influences of an emerging network of gang rivalries, Physica A, 390 (21-22):3894-3914, 2011.
36 Hegemann, Rachel A., Erik A. Lewis, and Andrea L. Bertozzi, An "Estimate & Score Algorithm" for simultaneous parameter estimation and reconstruction of missing data on social networks. Security Informatics, 2:1, 2013.
37 Hodas, N and Lerman, K. How Limited Visibility and Divided Attention Constrain Social Contagion. In ASE/IEEE International Conference on Social Computing, 2012.
38 Hodas, N. O.; and Lerman, K. "The Simple Rules of Social Contagion." Scientific Reports 4, 2014.
39 Hodas, N.; Kooti, F.; and Lerman, K. "Friendship Paradox Redux: Your Friends Are More Interesting Than You." In Proceedings of the 7Th International AAAI Conference On Weblogs And Social Media

(ICWSM), 2013. Honorable mention paper.
40 Hogg, T., and Lerman, K. Social Dynamics of Digg. EPJ Data Science, 1(5):, June, 2012.
41 Hogg, T.; Lerman, K.; and Smith, L. M. "Stochastic Models Predict User Behavior in Social Media." ASE Human, 2(1), 2013.
42 Hu, H.Y., Thomas Laurent, Mason A. Porter, Andrea L. Bertozzi, A Method Based on Total Variation for Network Modularity Optimization using the MBO Scheme. SIAM J. Appl. Math., 73(6), pp. 2224-2246, 2013.
43 Intagorn, S.; and Lerman, K. Placing User-generated Content on the Map with Confidence. In ACM GIS, 2014.
44 Juul, J., A. Kianercy, S. Bernhardsson and S. Pigolotti. "Replicator dynamics with turnover of players" Phys. Rev. E 88, 022806, 2013.
45 Kang, J.; and Lerman, K VIP: Incorporating Human Cognitive Biases in a Probabilistic Model of Retweeting. In International Conference on Social Computing, Behavioral Modeling and Prediction, April 2015a.
46 Kang, J.; and Lerman, K. "LA-CTR: A Limited Attention Collaborative Topic Regression for Social Media." In Twenty-Seventh AAAI Conference on Artificial Intelligence (AAAI), 2013a.
47 Kang, J.; and Lerman, K. User Effort and Network Structure Mediate Access to Information in Networks. In Proceedings of the 9th International AAAI Conference on Weblogs and Social Media (ICWSM), 2015b.
48 Kang, J.; and Lerman, K."Structural and Cognitive Bottlenecks to Information Access in Social Networks." In Proceedings of 24th ACM Conference on Hypertext and Social Media, 2013b.
49 Kang, J.; Lerman, K.; and Getoor, L. "LA-LDA: A Limited Attention Model for Social Recommendation." In International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction (SBP), 2013c. Terry Lyons Memorial Award for Best Student Paper.
50 Kang, Jeon-hyung, and Kristina Lerman. Factors Affecting Access to Information in Social Networks, in revision, ACM Transactions on the Web, 2015c.
51 Kianercy, A., and A. Galstyan. Coevolutionary networks of reinforcement-learning agents. Physical Review E 88, 012815, doi: 10.1103/PhysRevE.88.012815, 2013.
52 Kianercy, A., and Galstyan, A. Dynamics of Boltzman Q Learning in Two-Player Two-Action Games. Physical Review E. 85, 041145, 2012.
53 Kianercy, A., Galstyan, A. Allahverdyan, A. Adaptive Agents on Evolving Networks. In Proc. of AAMAS, 2012.
54 Kim, E., Chang, Y., Graham, J., Iyer, R. and Maheswaran, R. Moral Values from Simple Game Play. International Conference on Social Computing, Behavioral-Cultural Modeling, & Prediction (SBP), 2012.
55 Kim, E.; Chang, Y.; Maheswaran, R; Chi, L.; Ning, Y. Negotiation and Adaptation in Network Games. In the Fifth International Workshop on Agent-based Complex Automated Negotiations (ACAN), 2012.
56 Kim, E.; Chi, L.; Maheswaran, R.; and Chang, Y. Dynamics of Social Interactions in a Network Game. In Proceedings of the Third IEEE International Conference on Social Computing (SocialCom), 2011.
57 Kim, E.; Chi, L.; Ning, Y.; Chang, Y.; and Maheswaran, R. Adaptive Negotiating Agents in Dynamic Games: Outperforming Human Behavior in Diverse Societies. In Proceedings of the International Conference on Autonomous Agents and Multi-Agents Systems (AAMAS), 2012.
58 Kooti, F., Hodas, N. and Lerman, K. "Network Weirdness: Exploring the Origins of Network Paradoxes" in Proc. International Conference of Weblogs and Social Media (ICWSM), 2014.
59 Kooti, F.; Aiello, L. M.; Grbovic, M.; Lerman, K.; and Mantrach, A. Evolution of Conversations in the Age of Email Overload. In Proceedings of 24th International World Wide Web Conference (WWW), 2015.
60 Kooti, Farshad, Kristina Lerman, Luca M. Aiello, Mihajlo Grbovic, Nemanja Djuric, and Vladan Radosavljevic. "Portrait of an Online Shopper: Understanding and Predicting Consumer Behavior", accepted in International Conference on Web Search and Data Mining (WSDM), 2015.
61 Kostić, T. and A. Bertozzi. "Statistical Density Estimation Using Threshold Dynamics for Geometric Motion." Journal of Scientific Computing 54(2-3): 513-530, 2013.
62 Lee, S. H., M. Cucuringu, M. A. Porter, "Density-Based and Transport-Based Core-Periphery Structures in Networks", Physical Review E, 89(3): 032810, 2014.
63 Lerman, K., Hogg, T. Leveraging Position Bias to Improve Peer Recommendation. PLoS ONE 9(6): e98914, 2014.
64 Lerman, K. and Ghosh, R. Network Structure, Topology and Dynamics in Generalized Models of

Synchronization. Phys. Rev. E 86, 2012.
65 Lerman,K. Intagorn, S., Kang, JH, and Ghosh, R. Using Proximity to Predict Activity in Social Networks. In Proc. of World Wide Web Conference, 2012.
66 Lerman, K.; Jain, P.; Ghosh, R.; Kang, J.; and Kumaraguru, P. "Limited Attention and Centrality in Social Networks."In Proceedings of International Conference on Social Intelligence and Technology (SOCIETY), 2013.
67 Lerman, Kristina, Xioran Yan and Xin-zeng Wu. The Majority Illusion in Social Networks, in revision, Plos One, 2015.
68 Lewis, E., G. Mohler, P.J. Brantingham, A. Bertozzi, Self-Exciting Point Process Models of Civilian Deaths in Iraq, Security Journal, 25:244-264, 2011.
69 Li, Z.; Chang, Y.; Maheswaran, R. "Graph Formation Effects on Social Welfare and Inequality in a Networked Resource Game." International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction, 2013.
70 Ma, Anna, Arjuna Flenner, Deanna Needell, Allon G. Percus, "Improving image clustering using sparse text and the wisdom of the crowds," Proceedings of the 48th Annual Asilomar Conference on Signals, Systems, and Computers, in press 2015.
71 Ma, Anna, Deanna Needell, Aaditya Ramdas, "Convergence properties of the randomized extended Gauss-Seidel and Kaczmarz methods," SIAM Journal on Matrix Analysis and Applications, in press, 2015.
72 McBride, M. "Authority in Mormonism: A Rational Choice Analysis," in P. Mason, ed., Mormon Studies in the 21st Century, University of Utah Press, forthcoming 2015a.
73 McBride, M., "Why Churches Need Free-riders," Journal of Behavioral and Experimental Economics, 58: 77-87, 2015b.
74 McBride, M., D. Hewitt, "The Enemy You Can't See: An Investigation of the Disruption of Dark Networks," Journal of Economic Behavior and Organization 93: 32-50, 2013
75 McBride, M., M. Caldara, The Efficacy of Tables versus Graphs in Disrupting Dark Networks: An Experimental Study, Social Networks 35: 406-422, 2013.
76 McBride, M., S. Skaperdas, "Conflict, Settlement, and the Shadow of the Future," Journal of Economic Behavior and Organization 105: 75-89, 2014
77 McCalla, S.G., P.J. Brantingham, and M.B. Short. The effects of sacred value networks within an evolutionary, adversarial game. Journal of Statistical Physics 151(3-4): 673-688, 2013.
78 Melamed, D., R.L. Breiger, and A.J. West, "Community Structure in Multi-Mode Networks: Applying an Eigenspectrum Approach." Connections 33: 18-23, 2013.
79 Merkurjev, E., T. Kostic, and A. L. Bertozzi. An MBO Scheme on Graphs for Segmentation and Image Processing. SIAM J. Imaging Sci. 6(4), 1903-1930, 2013.
80 Merkurjev, Ekaterina, Cristina Garcia-Cardona, Andrea L. Bertozzi, Arjuna Flenner, Allon G. Percus. "Diffuse interface methods for multiclass segmentation of high-dimensional data," Applied Mathematics Letters, 33, 29-34, 2014.
81 Milward, H. Brinton, "What Healthcare Leaders Can Learn About Research on Dark Networks." Healthcare Management Forum. Fall 2015.
82 Mohler, G.O., M. B. Short, S. Malinowski, M. Johnson, G. E. Tita, A.L. Bertozzi and P. J. Brantingham. Randomized Controlled Field Trials of Predictive Policing. Journal of the American Statistical Association, 2015. published online Oct 7, 2015.
83 Mohler, G.O., M.B. Short, P.J. Brantingham, F.P. Schoenberg, and G.E. Tita, Self-exciting point process modeling of crime. Journal of the American Statistical Association 106(493):100-108, 2011.
84 Narang, K., K. Lerman and P. Kumaraguru "Network Flows and the Link Prediction Problem" The 7th SNA-KDD Workshop '13 (SNA-KDD'13), August 11, 2013, Chicago, 2013.
85 Ni, B.; Chang, Y.; Maheswaran, R. "Social Welfare and Inequality in a Networked Resource Game with Human Players." ASE/IEEE International Conference on Social Computing (SocialCom), 2013.
86 Polunchenko, A.S., and A.G. Tartakovsky, State-of-the-Art in Sequential Change-Point Detection, Methodology and Computing in Applied Probability, 14(3): 649–684, 2012.
87 Polunchenko, A.S., G. Sokolov, and A.G. Tartakovsky, "Optimal Design and Analysis of the Exponentially Weighted Moving Average Chart for Exponential Data." Sri Lankan Journal of Applied Statistics 5(4):57-80, 2014.

88 Popp, J.K., H.B. Milward, G. MacKean, A.Casebeer, and R. Lindstrom, "Interorganizational Networks: A Review of the Literature to Inform Practice" IBM Center for the Business of Government. September, 2014.
89 Purcell, Christopher and Puck Rombach. On the Complexity of Role Colouring Planar Graphs, Trees and Cographs. 2015. Journal of Discrete Algorithms, in press, 2015.
90 Raghavan, V., A. Galstyan, and A.G. Tartakovsky, Hidden Markov Models for the Activity Profile of Terrorist Groups, Annals of Applied Statistics, vol. 7, no. 4, pp. 2402-2430, 2013.
91 Raghavan, V., G. V. Steeg, A. Galstyan, and A.G. Tartakovsky, Modeling Temporal Activity Patterns in Dynamic Social Networks, IEEE Transactions on Control Systems Technology, in press 2014.
92 Ridinger, G. and M. McBride. Money Affects Theory of Mind Differently by Gender. PLOS One 10(12): e0143973, 2015
93 Ridinger, G., R. John, M. McBride, N. Scurich, "Attacker Deterrence and Perceived Risk in a Stackelberg Security Game," Risk Analysis, in press 2015.
94 Schoon, Eric W. "The Paradox of Legitimacy: Resilience, Successes, and the Multiple Identities of the Kurdistan Workers' Party in Turkey". Social Problems 62(2), 266-285, 2015.
95 Schoon, Eric W. "The Asymmetry of Legitimacy: Analyzing the Legitimation of Violence in 30 Cases of Insurgent Revolution." Social Forces 93(2): 779-801, 2014.
96 Short, M.B., G.O. Mohler, P.J. Brantingham, and G.E. Tita, Gang Rivalry Dynamics Via Couple Point Process Networks, Discrete and Continuous Dynamical Systems 19(5): 1459-1477, 2014.
97 Short, M.B., P.J. Brantingham, and M.R. D'Orsogna. Cooperation and punishment in an adversarial game: How defectors pave the way to peaceful society. Physical Review E 82:66114-1-7, 2010.
98 Smith, Laura M., Kristina Lerman, Cristina Garcia-Cardona, Allon G. Percus, Rumi Ghosh. "Spectral clustering with epidemic diffusion," Physical Review E, 88, 042813, 2013.
99 Smith, L. M.; Zhu, L.; Lerman, K.; and Kozareva, Z, "The Role of Social Media in the Discussion of Controversial Topics." In ASE/IEEE International Conference on Social Computing, 2013.
100 Smith, Laura M., Andrea L. Bertozzi, P. Jeffrey Brantingham, George E. Tita, and Matthew Valasik, Adaptation of an Ecological Territorial Model to Street Gang Spatial Patterns in Los Angeles, Discrete and Continuous Dynamical Systems 39(2): 3223-3244, 2012.
101 Smith, Laura M., Linhong Zhu, Kristina Lerman and Allon G. Percus. Partitioning Networks with Node Attributes by Compressing Information Flow, in revision. ACM Transactions on Knowledge Discovery from Data, 2015.
102 Stomakhin, Alexey., Martin B. Short, and Andrea L. Bertozzi, Reconstruction of Missing Data in Social Networks Based on Temporal Patterns of Interactions, Inverse Problems 27: 115013, 2011.
103 Tartakovsky, A.G., and M. Pollak, Nearly Minimax Changepoint Detection Procedures. In Proceedings of the IEEE International Symposium on Information Theory, St. Petersburg, Russia, July 31-August 5, 2011.
104 Tartakovsky, A.G., I. Nikoforov, and M. Basseville, Sequential Analysis: Hypothesis Testing and Change-Point Detection, Chapman & Hall/CRC, 2015.
105 Tartakovsky, A.G., M. Pollak, and A.S. Polunchenko, Third-order Asymptotic Optimality of the Generalized Shiryaev–Roberts Detection Procedures, Theory of Probability and Its Applications, 56(3): 457–484, 2012.
106 Tartakovsky, A.G., Nearly Optimal Sequential Tests of Composite Hypotheses – Revisited, Proceedings of the Steklov Institute of Mathematics 287(1):268-288, 2015.
107 Van Gennip, Y., B. Hunter, R. Ahn, P. Elliott, K. Luhz, M. Halvorson, S. Reid, M. Valasik, J. Wo, G. E. Tita, A.L. Bertozzi , P.J. Brantingham. Community detection using spectral clustering on sparse geosocial data. SIAM Journal of Applied Math, 73(1): 67-83, 2013.
108 Van Gennip, Y., Nestor Guillen, Braxton Osting, and Andrea L. Bertozzi, Mean curvature, threshold dynamics, and phase field theory on finite graphs, Milan J. of Math, 82(1):3-65, 2014.
109 Van Gennip, Yves, and Andrea L. Bertozzi. Gamma-convergence of graph Ginzburg-Landau Functionals. Advances in Differential Equations, 17:1115-1180, 2012.
110 Ver Steeg, G, and A. Galstyan. 2012. Information Transfer in Social Media, In Proc. of International Conference on World Wide Web, 2012.
111 Ver Steeg, G. , A. Galstyan, and A. E.Allahverdyan, Statistical mechanics of semi-supervised clustering in sparse graphs. Journal of Statistical Mechanics: Theory and Experiment 2011 (08):P08009, 2011.

112 Ver Steeg, G. and A. Galstyan. Information-Theoretic Measure of Influence based on Content Dynamics, in Proc. of the 6th ACM Conference on Web Search and Data Mining, WSDM'13, Rome Italy, 2013a.
113 Ver Steeg, G., A. Galstyan, F. Sha, S. DeDeo. Demystifying Information-Theoretic Clustering, in Proc. of ICML'14, 2014.
114 Ver Steeg, G., and A. Galstyan, "A Sequence of Relaxations Constraining Hidden Variable Models", In Proc. of the Twenty-Seventh Conference on Uncertainty in Artificial Intelligence, 2011.
115 Ver Steeg, G., and A. Galstyan. Statistical Tests for Contagion in Observational Social Network Studies, in Proc. of AISTATS'13, 2013b.
116 Ver Steeg, G., and Ghosh, R. and Lerman, K, "What stops social epidemics?", In Proc. of International Conference on Weblogs and Social Media, 2011.
117 Ver Steeg, G., Moore, C., Galstyan, A, Allahverdyan A. Phase Transitions in Community Detection: A Solvable Toy Model, EuroPhysics Letters 106, 48004, 2014.
118 Von Brecht, J. Benjamin Sudakov, and A. L. Bertozzi, Swarming on Random Graphs II, J. Stat. Phys., 158(3):699-734, 2015.
119 Von Brecht, J., T. Kolokolnikov, A.L. Bertozzi, H. Sun. Swarming on random graphs. Journal of Statistical Physics, 151(1-2):150-173, 2013.
120 Walsh, T.J., J. Taheri, J.B. Wright, P.R. Cohen. 2011. Leadership Games and their Application in Super-Peer Networks. Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence, San Francisco, Aug 7-11, 2011.
121 Woodworth, J. T., G. O. Mohler, A. L. Bertozzi and P. J. Brantingham, Nonlocal Crime Density Estimation Incorporating Housing Information, Phil. Trans. Roy. Soc. A, Phil. Trans. Roy. Soc. A, 372(2028), 20130403, 2014.
122 Zhu, L.; and Lerman, K. A Visibility-based Model for Link Prediction in Social Media. In Proceedings of the ASE/IEEE Conference on Social Computing, 2014.
123 Zipkin, Joseph R., Frederic P. Schoenberg, Kathryn Coronges, and Andrea L. Bertozzi, Point-process models of social network interactions: parameter estimation and missing data recovery, EJAM, in press, 2015.

Changes in research objectives (if any):

None

Change in AFOSR Program Manager, if any:

Terry Lyons Year 1
Joe Lyons Years 2-3
Benjamin Knott Years 4-5

Extensions granted or milestones slipped, if any:

None

AFOSR LRIR Number

LRIR Title

Reporting Period

Laboratory Task Manager

Program Officer

Research Objectives

Technical Summary

Funding Summary by Cost Category (by FY, $K)

	Starting FY	FY+1	FY+2
Salary			
Equipment/Facilities			
Supplies			
Total			

Report Document

Report Document - Text Analysis

Report Document - Text Analysis

Appendix Documents

2. Thank You

E-mail user

Dec 21, 2015 16:11:30 Success: Email Sent to: branting@ucla.edu